Three essays on firms' exposure to common risks

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Lars Kabitz
from Surses, GR

approved in April 2017 at the request of
Prof. Dr. Robert F. Göx
Prof. Dr. Hui Chen

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Preface

Agency theory recommends firms to filter out systematic risks in evaluating the performance of the agents. This practice permits firms to reduce the compensation risk that arises from the volatility of systematic risk factors and makes the agents' contract more efficient. Firms are however exposed to a variety of different exogenous risks, such as commodity prices, exchange rates or macroeconomic factors, and it is not evident to filter out these elements from an executive's compensation. In fact, the numerous empirical studies in this branch of the literature have so far found no clear evidence that firms actually filter out systematic risks as recommended by agency theory.

The first part of this thesis is dedicated to this discrepancy between theory and practice and provides a literature review of empirical studies on relative performance evaluation (RPE). The focus of the survey is to describe the most prominent explanations for the RPE puzzle, i.e. I investigate how researchers explain the missing evidence in favor of RPE despite its theoretical advantages. More precisely, I summarize the existing empirical research to describe how the optimality of implementing RPE can depend on many aspects, such as strategic considerations, CEO-specific characteristics or managerial power.

The main part of the thesis then investigates a particular difficulty that arises if a firm tries to filter out systematic risks and what this implicates in terms of efficient contracting. Namely, I study how the firms' exposure to systematic risks varies over time and how this prevents efficient filtering. To do so, I investigate two relevant forms of common risk filtering, RPE and the removal of foreign exchange rate movements from firm performance.

Relative performance evaluation (RPE) aims to filter out the systematic risks by evaluating the agent's performance relative to the performance of a peer group. The reasoning behind this approach is that firms are exposed to common risks and observing the performance of the peer group provides information on the extent of the exogenous shock. This allows firms to filter the common risks from their own performance, even if the common risk factors are not directly measurable (Holmström, 1982). However, a time-varying exposure to systematic risks could preclude the complete filtering in a RPE setting. I address this concern in the second paper of this thesis.

To do so, I estimate in a first step the exposure of a firm's performance to the performance of potential peer firms in order to construct a firm-specific peer group. Second, I investigate how the volatility in the exposure can affect the composition and aggregation of a peer group over time. Finally, I show how these movements in the peer group composition and aggregation can reduce the effectiveness of the filtering purpose in RPE settings.

If common risk factors are perfectly measurable, such as commodity prices or foreign exchange rates, the systematic risk can theoretically be perfectly eliminated from measures of firms performance. The executive's performance should then be evaluated net of the influence of common risk to avoid reward for (observable) luck (Bertrand and Mullainathan, 2001). In the last part of the thesis, I address this topic and investigate the foreign exchange rate exposures of Swiss firms. As a small and export-oriented country, the currency exchange rates are particularly important for Switzerland and therefore represent a relevant common risk factor for Swiss firms.

More precisely, the third study measures the exchange rate exposure of Swiss firms to its most relevant export and import currencies and assesses its variation over time. I find that the firm-level exposure varies considerably over time and that the volatility in the exposure limits the ability to filter out currency risks. This can lead to wrong decisions with regard to risk filtering and hedging activities, respectively.

Overall, the findings in this thesis show that a time-varying exposure to systematic risks precludes perfect filtering. In the worst case, trying to filter out common risk factors from a firm performance to reduce its variance can even be counterproductive due to the time-variation of the risk exposure, i.e.

filtering can even increase the variance of the firm performance instead of reducing it.

This has important implications for the use of RPE. A firm not only needs to know how it is exposed to systematic risks, but as well how their exposure varies over time. Ignoring this aspect might lead to wrong decision making. And even if firms are aware of the exposure volatility, they need to evaluate whether it is still optimal for them to filter out systematic risks or not.

Survey on empirical RPE tests

Abstract

This paper provides a literature review of empirical studies on relative performance evaluation (RPE). The focus of this survey is to describe the most prominent explanations for the RPE puzzle, i.e. I investigate how researchers explain the missing evidence in favor of RPE despite its theoretical advantages. Namely, I summarize the existing empirical research to describe how the optimality of implementing RPE depends on many aspects, such as strategic considerations, CEO-specific characteristics or managerial power.

1 Introduction

According to agency theory, the use of relative performance evaluation provides clear benefits. Many firms reward their executives for absolute firm performance to align the interests of the shareholder with those of the executives. The absolute firm performance is however noisy, since it is affected by external factors beyond the manager's control. In a RPE setting, the principal rewards the agent not only based on the firm's own performance, but also on the performance of a peer group. This combined performance measure removes the common risks without reducing the agent's incentives, which increases the overall efficiency of the contract (Holmström, 1982).

Empirical researchers have consequently investigated whether firms actually use RPE as predicted by theory. The numerous attempts to detect RPE have however largely been unsuccessful. This lack of evidence in favor of RPE stands in contrast to its theoretical predication and has become know as the RPE puzzle (see e.g. Gibbons and Murphy (1990) or Rajgopal et al. (2006)). Numerous researchers have attempted to resolve this puzzle by investigating possible explanations for the absence of RPE.

In the present survey, I provide an overview of the existing empirical RPE studies and how they explain the RPE puzzle. In a first step, I review the empirical methodology of the prevailing RPE tests by describing two typical examples of such studies. This allows to assess the question how the studies differ from each other in terms of methodology and builds a foundation for the analysis of the RPE puzzle. Second, I describe possible explanations for the RPE puzzle that have been empirically investigated in the academic literature.

The empirical literature on RPE has been rapidly growing during the last two decades and a single survey cannot cover each and every of these studies. Thus, I need to make some restrictions in the scope of this paper. I collect the most prevailing explanations for the RPE puzzle and classify them into three different categories. This categorization is of course just one possible approach out of many, but it can help the reader to get an overview of the topic. For each category I pick some representative studies and present the researchers' main hypotheses, their regression model, the test they use and their main findings.

One of the most prevalent hypothesis to explain the lack of RPE as failures in corporate governance, as e.g. in Bebchuk et al. (2002) or Bertrand and Mullainathan (2001). In this view, the filtering of external risks is optimal, but agents with some power over the pay-setting process prevent the implementation of RPE in their contract. A second widely spread explanation for the RPE puzzle is that RPE creates incentives for manipulation. For example, Aggarwal and Samwick (1999a) describe a setting where the principal adjusts the agent's exposure to the peer group performance to account for its competitive position in the product market. Another example is the setting in Gopalan et al. (2010), where the agents can take actions to affect the firm's exposure to the peer group performance. I use the term strategic considerations to refer to all kind of such manipulations. One difference to the corporate governance explanation is that, due to strategic considerations, it might be optimal for a firm not to do RPE.

Third, some authors argue that the use of RPE depends on the CEO hedging possibilities or CEO outside options, e.g. Garvey and Milbourn (2003) or Oyer (2004). The benefits of RPE are generally acknowledged in those papers, but the extent to which it is optimal for a firm to provide such a contract to the executive, depends on their individual characteristics or actions.

The objective of the present survey is to provide a useful overview of the existing literature on empirical RPE tests and their explanation for the RPE puzzle. The survey looks at the RPE puzzle from different points of view, which is in my opinion important to better understand a problem and to be able to deal with the proposed solutions in a critical and differentiated way. It can thus serve as starting point for interested readers and researchers and might as well give new ideas for further research. The reminder of the paper is organized as follows. The next section briefly describes the theoretical framework for RPE. Section 3 reviews the empirical approach of typical RPE tests. Section 4 presents some relevant studies in detail. Section 5 summarizes and concludes the survey.

2 Theoretical foundations of RPE

2.1 The performance-based contract

Agency theory builds the framework for the investigation of executive compensation contracts, which includes RPE contracts. The starting point is a principal, who hires an agent to run a firm. This firm belongs to the principal, who is typically represented by the shareholders or the board of directors. The principal is interested in maximizing the firm performance x, which is composed of the following three terms (as e.g. in Dikolli et al. (2013)):

$$x = a_x + c_x \cdot \eta + \epsilon_x \tag{1}$$

The agent can positively affect the expected firm performance $E(x)$ by exerting a personal effort a_x. However, providing an effort a_x is personally costly to the agent. The personal costs are measured by the function $C(a_x)$, which is strictly convex in a_x. Additionally, x depends on a systematic risk component η. This can be viewed as a market-wide risk factor, such as foreign exchange rates, commodity prices or other macroeconomic conditions. c_x is the firm's exposure to this systematic risk, i.e. the degree to which the firm's performance reacts to external shocks. It is assumed that the agent cannot control $c_x \cdot \eta$. Finally, the term ϵ_x reflects uncontrollable firm-specific risks.

It is in the best interest of the shareholders to motivate the agent to provide some effort. Because the effort is not directly observable, the principal cannot write a contract based on a_x to obtain the desired level of the agent's effort. Instead, the principal offers her a performance-based compensation

$s(x)$ which is linearly increasing in x.

$$s(x) = w + v_x \cdot x \tag{2}$$

w is a fixed wage and v_x is the agent's share of the firm performance x. The contract of the form $s(x)$ has the following consequences. On the one hand it becomes costly for the principal to provide incentives for the agent to exert effort. An increase of x has to be shared with the agent as her compensation is increasing in x. On the other hand, awarding the manager for the firm performance makes the contract risky, because the compensation does not only depend on her effort, but also on η and ϵ_x, both of which are not under the control of the manager.

In the linear agency model (Holmström and Milgrom, 1987), all noise terms are normally distributed, the agent's utility function is negative exponential, and the contract takes the form in (2). Under these conditions, the certainty equivalent of the agent can be described as follows (r being the agent's coefficient of absolute risk aversion):

$$CEA = E(s(x)) - C(a) - \frac{r}{2} \cdot Var(s(x)) \tag{3}$$

The risk-neutral principal will maximize own utility $U^P = E(x) - E(s(x))$ subject to the following constraints:

$$a \in \arg\max_a CEA \tag{4}$$

and

$$CEA \geq \overline{U} \tag{5}$$

The incentive constraint (4) indicates that the agent will chose her level of effort in order to maximize her utility and the participation constraint (5) ensures that the agent can attain at least her reservation utility $\overline{U}$ from the contract. Normalizing $\overline{U}$ to zero, the substitution of both constraints into the principal's utility function yields

$$U^P = E(x) - C(a) - \frac{r}{2} \cdot Var(s(x)). \tag{6}$$

The equation (6) shows that a lower compensation variance increases the principal's utility and it is thus in his best interest to minimize it. Furthermore, the expected profit $E(x)$ can only be positive if $v_x > 0$, because otherwise the agent would not provide any effort and $E(x)$ would be zero, which cannot be in the interest of the principal.

The agent's compensation risk can be measured by the variance of the agent's pay, so that:

$$Var(s(x)) = v_x^2 \cdot Var(x) \tag{7}$$

It follows that increasing the agent's incentive rate v_x not only raises the agent's level of effort and expected compensation, but also the risk premium that the principal must bear in order to motivate the agent. An optimal performance-based contract aims thus to solve the trade-off between the incentive effect and the risk sharing. The next subsection shows how a RPE contract improves the simple performance-based compensation in equation (2).

2.2 The RPE contract

In a RPE contract, the agent's compensation is not only based on the own firm performance, but also on the performance of a peer group. For simplicity, I use only a single peer firm instead of an entire group to explain the RPE contract. The peer firm's performance y is observable and takes following form:

$$y = a_y + c_y \cdot \eta + \epsilon_y \tag{8}$$

This is essentially the same as in equation (1). The peer firm is exposed to the same systematic risk η as the focal firm. However, the exposure c_y is not necessarily identical to c_x. The contribution of the peer firm's manager and the idiosyncratic risk ϵ_y are firm-specific as well. The two firm performances are related via the common risk η, i.e. $Cov(x, y) \neq 0$. The peer performance y is included in the RPE contract, which now takes the following form:

$$s(x, y) = w + v_x \cdot x + v_y \cdot y \tag{9}$$

Following the same argument as in section 2.1, the variance of manager's compensation is accordingly:

$$Var(s(x, y)) = v_x^2 \cdot Var(x) + v_y^2 \cdot Var(y) + 2 \cdot v_x \cdot v_y \cdot Cov(x, y) \tag{10}$$

The principal will choose the parameters v_x and v_y in a way to minimize the variance of the compensation for risk-averse agent. Minimizing equation (10) with respect to v_y yields

$$v_y^* = -v_x \cdot \frac{Cov(x, y)}{Var(y)} \tag{11}$$

Equivalent to (11), the optimal ratio of the the parameters v_x and v_y is

$$\frac{v_y^*}{v_x} = -\frac{Cov(x, y)}{Var(y)} \tag{12}$$

In the next step I substitute v_y^* from equation (11) into the equation (10) to obtain the variance of the agent's compensation:

$$Var(s(x, y)) = v_x^2 \cdot (Var(x) - \frac{Cov(x, y)^2}{Var(y)}) \tag{13}$$

The comparison between the variances of the simple performance-based contract and the RPE contract shows that $Var(s(x, y)) < Var(s(x))$. Using relative performance evaluation reduces the overall variance of the agent's compensation for any $v_x \neq 0$ and is thus always more efficient.

The empirical approach to test for the presence of RPE in executive compensation contracts uses equation (9) as regression model:

$$z_{i,t} = \beta_0 + \beta_1 \cdot x_{i,t} + \beta_2 \cdot y_{i,t} + \varepsilon_{i,t} \tag{14}$$

$z_{i,t}$ is the executive's compensation of firm i in period t. $x_{i,t}$ is the focal firm performance and $y_{i,t}$ is the peer firm performance. One can see from equation (12) that the theoretical prediction to be tested is

$$\frac{\beta_2}{\beta_1} = -\frac{Cov(x, y)}{Var(y)}. \tag{15}$$

Rejecting this hypothesis means that the focal firms does not completely filter out the systematic risk from the executive's compensation. This test form is a called a strong-form test in the RPE literature (see e.g. Janakiraman et al. (1992) or Albuquerque (2009)). An alternative possibility is to conduct a weak-form test, which can provide evidence that the common risk factors are at least partly filtered out from the agent's compensation (Janakiraman et al., 1992). I next describe both tests in more detail, each with the help of an example.

3 Empirical RPE tests

3.1 The strong-form test

Antle and Smith (1986) were among the first authors to conduct an empirical RPE test. In this section, I present their methodology for a strong-form test, which many subsequent studies have adopted. Their approach can thus still be considered as commonly accepted and up to date, even if the study has already been published three decades ago.

Antle and Smith (1986) use a two-step approach to test whether the systematic risk component is completely filtered out from the executive's compensation. The first step serves to separate the firm's systematic and unsystematic risk. Since those two components cannot be observed directly, they must be estimated by decomposing the total firm performance x. The authors obtain this decomposition by regressing the firm performance on the peer performance:

$$x_{i,t} = \gamma_0 + \gamma_1 \cdot y_{i,t} + u_{i,t} \tag{16}$$

Antle and Smith (1986) use two performance measures, namely equity returns (RET) and the return on assets (ROA).[1] [2] The independent variable y measures the peer performance. In most implicit RPE tests, it takes the form of the S&P500 index, an industry, or an industry-size peer group. For example, Antle and Smith (1986) use an industry index based on the two-digit SIC code. The performances of those firms is then aggregated to an index by using a correlation-based aggregation rule.

On the basis of the results from the regression in (16), one can compute the systematic and the unsystematic risk component as x^s and x^u, respectively:

$$x^s_{i,t} = \hat{\gamma}_1 \cdot y_{i,t} \tag{17}$$

and

$$x^u_{i,t} = x - \hat{\gamma}_1 \cdot y_{i,t} = \hat{\gamma}_0 + \hat{u}_{i,t} \tag{18}$$

x^s takes the value of the estimated regression coefficient $\hat{\gamma}_1$ multiplied by the peer performance. x^u is accordingly defined as the remaining part of the regression, where $\hat{\gamma}_0$ is the estimated regression constant and $\hat{u}_{i,t}$ is the residual.

The second step measures whether the peer performance y has been filtered out from the executive's compensation. To do so, the researcher needs the corresponding compensation data. Regarding the availability of the data,

[1] Later on, RET has become the established performance measure for RPE tests, since nowadays nearly all researchers use the equity returns to conduct their RPE tests.

[2] Albuquerque (2009) and Dikolli et al. (2013) provide a useful overview of empirical RPE tests. They describe some details on the empirical approach and the main findings for a large number of RPE studies. Appendix A and B of the present survey enlarge their overview by giving further details on the econometric specifications.

there has been a strong trend towards an increased disclosure in this field over the last two decades. RPE studies from the 1980s use hand-collected data from the annual proxy statements (e.g. Antle and Smith (1986)) or rely on survey data (e.g. Gibbons and Murphy (1990) use compensation surveys). Increased disclosure rules and the emergence of databases such as *ExecuComp* doubtlessly enlarged the amount of compensation data available and improved its measurement accuracy.

The dependent variable for the second regression is the executive's compensation $z_{i,t}$. Antle and Smith (1986) define z as the level of compensation, while most other studies use the difference in the remuneration from one year to another. The independent variables are the systematic and unsystematic risk components which have been estimated in the first step.

$$z_{i,t} = \beta_0 + \beta_1 \cdot x^u_{i,t} + \beta_2 \cdot x^s_{i,t} + \varepsilon_{i,t} \tag{19}$$

If the entire systematic risk is filtered out of the executive's compensation, the regression coefficient β_2 cannot be distinguished from zero, i.e. one tests the hypothesis $\beta_2 = 0$. To illustrate the link between the theoretical part in the previous section and the regression above, I use again the RPE contract from regression model (14) and substitute the results from the first-step regression (16) into (14). This leads to

$$\begin{aligned} z_{i,t} &= \beta_0 + \beta_1 \cdot (\hat{\gamma}_0 + \hat{\gamma}_1 \cdot y_{i,t} + \hat{u}_{i,t}) + \beta_2 \cdot y_{i,t} + \varepsilon_{i,t} \\ &= \beta_0 + \beta_1 \cdot (\hat{\gamma}_0 + \hat{u}_{i,t}) + \beta_1 \cdot \hat{\gamma}_1 \cdot y_{i,t} + \beta_2 \cdot y_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{20}$$

Next, I substitute the optimal β_2 from equation (15) into (20). I additionally use the estimated coefficient $\hat{\gamma}_1$ from the regression (16), which can be written as

$$\hat{\gamma}_1 = \frac{Cov(x,y)}{Var(y)}. \tag{21}$$

Thus I have

$$
\begin{aligned}
z_{i,t} &= \beta_0 + \beta_1 \cdot (\hat{\gamma}_0 + \hat{u}_{i,t}) + \beta_1 \cdot \hat{\gamma}_1 \cdot y_{i,t} + (-\beta_1 \cdot \frac{Cov(x,y)}{Var(y)}) \cdot y_{i,t} + \varepsilon_{i,t} \\
&= \beta_0 + \beta_1 \cdot (\hat{\gamma}_0 + \hat{u}_{i,t}) + (\beta_1 - \beta_1) \cdot \hat{\gamma}_1 \cdot y_{i,t} + \varepsilon_{i,t} \\
&= \beta_0 + \beta_1 \cdot x^u_{i,t} + (\beta_1 - \beta_1) \cdot x^s_{i,t} + \varepsilon_{i,t} \qquad (22)
\end{aligned}
$$

One can see that the optimal contract does not reward the agent for the systematic risk, since its weight is given by $(\beta_1 - \beta_1) = 0$. This transformation helps to see how the implementation of the optimal contract is empirically investigated by running the regression model (19) and testing the hypothesis $\beta_2 = 0$.

3.2 The weak-form test

As I described in the introduction, there exist many possible explanations why firms might not completely filter out the systematic risks out of a compensation contract. A common approach in the RPE literature is thus to test whether the systematic risks are at least partially filtered out. I first show how the two-step procedure explained above can be used to perform a weak-form test. Second, I describe an alternative one-step approach for this test.

The regression model (19) can also be used for the weak-form test. The only difference is that one does not test whether $\beta_2 = 0$, but rather the hypothesis $\beta_2 < \beta_1$. Finding support for the weak-form RPE suggests that the executives are paid differently for an increase in the unsystematic and systematic risk. For example, Antle and Smith (1986) find that the average pay level of CEOs is higher for a given increase in $x^u_{i,t}$ than for the same increase in $x^s_{i,t}$.

The study from Gibbons and Murphy (1990) uses a widespread alternative regression model to test the weak-form RPE:

$$z_{i,t} = \alpha_0 + \alpha_1 \cdot x_{i,t} + \alpha_2 \cdot y_{i,t} + \varepsilon_{i,t} \tag{23}$$

The main difference to the setting above is that simply one regression is needed, i.e. it is a one-step approach instead of the two-step model before. The hypothesis is that the peer performance y is negatively related to the manager's remuneration.[3] A regression coefficient $\alpha_1 > 0$ means that the executive compensation is increasing in x (which includes the systematic risk component), and a regression coefficient α_2 significantly lower than zero means that the firm at least partly filters out the systematic risk component.

3.3 Explicit RPE tests

A general difficulty in empirical RPE tests is that the researcher cannot observe how the board of directors computes the peer group performance. The researcher thus needs to make assumptions on this matter and can only implicitly test for RPE. This creates possible summarization errors which can lead to wrong inferences (Dikolli et al., 2013).

Beside the numerous studies which investigate possible reasons for the lack of RPE, some authors argue that firms might actually use RPE, but that it is simply not detected by the researchers because they make wrong assumptions on the peer group composition. Gong et al. (2011) take advantage of the SEC's 2006 disclosure rule on executive compensation, which requires firms to report details on the peer group they use for compensation benchmarking or RPE. This disclosure rule enables the authors to know the peer group composition of the firms and to perform an explicit RPE test.

The problem of the unobservable peer group performance has however not fully been resolved by the introduction of the 2006 SEC disclosure rule. While

[3]This assumes that the firm performances x and y are positively correlated. In case of a negative correlation, one would test whether α_2 is positive.

the composition of a peer group can now be observed, it remains unclear which weight a firm assigns to each of its peers, as already pointed out by Dikolli et al. (2013). Summarization errors are thus still possible, even if the researcher exactly knows which firms use RPE and how their peer group is selected.

The regression model itself is not different for explicit and implicit RPE tests. For example, Gong et al. (2011) follow a typical weak-form test, i.e. the authors estimate

$$z_{i,t} = \alpha_0 + \alpha_1 \cdot x_{i,t} + \alpha_2 \cdot y_{i,t} + \alpha_c \cdot C_{i,t} + \varepsilon_{i,t}. \tag{24}$$

Different from most other studies, Gong et al. (2011) do not aggregate the peer firms' performances to an index according to a specific aggregation rule, but rather use the median stock return of the disclosed peer group as peer performance $y_{i,t}$. $C_{i,t}$ are the control variables (which are, amongst others, firm size, growth options and CEO tenure). In order to show how the explicit approach can outperform the implicit RPE test, the authors estimate regression (24) by using two different specifications.

First, they reperform existing RPE tests and compute $y_{i,t}$ as an industry-size index (as in Albuquerque (2009)). Second, they compute $y_{i,t}$ as the median return of the explicitly disclosed peer firms as described above. The results provide no evidence in favor of RPE when the industry-size index is used (α_2 cannot be distinguished form zero). In contrast, the coefficient α_2 is significantly negative if the disclosed peer group is used. This shows how the results in a RPE test are sensitive to the researcher's choice of a peer group composition.

4 Empirical studies on the RPE puzzle

4.1 Strategic considerations

A reason which has often served as an argument for not using RPE is the possibility that RPE creates incentives for the CEO to take decisions that affect the outcome of the peer group or the extent to which the firm is exposed to the peer group. Gibbons and Murphy (1990) describe some possible limitations of RPE in a setting, where the agent can affect the peer outcome and thus limit the usefulness of RPE.

For example, if the decision of a manager has a positive effect on the performance of the industry, RPE can reduce the incentive to take such a decision. Imagine a CEO who can invest in lobbying in order to obtain a better regulatory framework for the industry. RPE would reduce the incentive to invest, because other firms in the industry would benefit as well from her effort and the CEO cannot create an advantage for her firm relative to its competitors. Even though in absolute terms the investment might be profitable, the manager has no incentive to realize it.

Another example is that a RPE contract might incentivize agents to collude and supply less effort than would be supplied in absence of the collusion. Establishing a cartel and creating high barriers for new competitors to enter the market are examples for such a collusion. Aggarwal and Samwick (1999b) analyze such a setting in more detail to show the effect of strategic considerations in RPE settings. I next provide an overview of their study.

Aggarwal and Samwick (1999b) present an inherent conflict between strategic competition and the principal-agent problem. The authors analyze two different oligopolistic market structures (Bertrand and Cournot competition). The main question of the study is whether a firm i can raise their profits by offering their manager a RPE contract, written as

$$z_i = w_i + \alpha_i \cdot x_i + \beta_i \cdot y_i \tag{25}$$

where $w_{i,j}$ is the fixed salary and x_i is the profit of the own firm i and y_i the one of the rival firm.[4] This is a standard setting for the weak-form RPE test for which the basic hypothesis is $\beta_i < 0$.

The Bertrand competition describes a market where firms compete in prices and the firm's choices are strategic complements. Aggarwal and Samwick (1999b) show that the equilibrium where outputs are strategic complements and price competition is prevailing in a duopoly with contracts as in (25) result in higher profits for both firms than with contracts based on the own firm's profits only. However, contrary to the basic RPE setting, the optimal weight β on the rival firm's profit is now positive. The intuition behind this solution is that the positive weight on β softens the price competition. To put it another way, a negative weight in RPE contracts, with the goal of filtering out common shocks, induces managers to act more aggressively in the product market, which hurts firm profitability.

In a Cournot competition, where the firms compete in quantities and their choices are strategic substitutes, the optimal contract looks different. Namely, the weight β on the rival firm's profit is now negative, as it is in a basic RPE contract described in section 2.2. However, the result is not driven by a principal-agent problem (to filter out systematic risks), but by the nature of the strategic interaction, i.e. it is a strategic choice rather than a response to moral hazard. The principal wants to toughen the competition in order become a quantity leader. The RPE contract creates the usual prisoner's dilemma among Cournot competitors. If firms would agree not to use RPE, profits would be higher for both firms. But as soon as one firm moves to an RPE contract, it is optimal for the rival firm to do RPE as well.

[4] Aggarwal and Samwick (1999b) use all firms in the same 4-digit SIC code as rival firms and compute y_i as a value-weighted return.

The intensity of RPE depends on the degree of competition in both settings. In the Bertrand model, a high degree of competition in the industry leads to a lower weight of α relative to β. In Cournot settings, a more competitive industry puts as well more weight on the rival firm, but with a negative sign.

The two different results make an empirical test for RPE difficult, since there is no clear direction for the RPE weight β. The authors use their result that an increased product substitutability, which also means a higher competition in the market, is associated with a lower ratio α/β in absolute terms in both settings the Bertrand and the Cournot competition, respectively. The regression model to test this hypothesis takes the following form:

$$\begin{aligned} z_{i,j,t} &= \beta_0 + \beta_1 \cdot x_{j,t} + \beta_2 \cdot y_{j,t} + \beta_3 \cdot F(H_j) \cdot x_{j,t} + \beta_4 \cdot F(H_j) \cdot y_{j,t} \\ &\quad + \beta_5 \cdot F(H_j) + \beta_6 \cdot CEO_{i,t} + SIC_j + Y_t + \varepsilon_{i,j,t} \end{aligned} \tag{26}$$

$z_{i,j,t}$ is the total compensation of the executive i, who works for the firm j in year t. $F(H_j)$ is the cumulative distribution function of the Herfindahl index. This index measures the intensity of the market competition, which Aggarwal and Samwick (1999b) use as proxy for product substitutability. The value zero is assigned to the least concentrated industry and the most concentrated (i.e. least competitive) market takes the value of one.[5] The variable $CEO_{i,t}$ is one if the executive is the CEO of the firm and zero for non-CEO executives. The authors also include industry and year fixed effects.

Aggarwal and Samwick (1999b) first evaluate whether the weak-form RPE holds by testing the hypothesis $\beta_2 + \beta_4 \cdot F(H_j) < 0$. The estimate β_2 alone is positively associated with executive pay, which is against the RPE prediction, but instead supports the Bertrand model.[6] Together, the estimates $\beta_2 + \beta_4 \cdot$

[5]The construction of the cumulative distribution function (cdf) is a popular approach in order to obtain conveniently interpretable regression coefficients. Aggarwal and Samwick (1999a) have first used the cdf in a RPE test and many subsequent RPE studies have followed this approach.

[6]However, in a specification where only the short term compensation is used as dependent variable, the authors find $\beta_2 < 0$, which supports the presence of weak-form RPE.

$F(H_j)$ are also positive for all degrees of competition.

To test whether the extent of RPE differs with the competition in a market, the authors investigate the hypothesis $\beta_4 < 0$. This estimate is significantly negative for all specifications, which further supports the Bertrand model of the authors. The interpretation of Aggarwal and Samwick (1999b) for this result is that RPE is limited by strategic interaction. Namely, an intense competition (and thus a low $F(H_j)$) makes RPE less useful for the firm according to the Bertrand model, because RPE would create incentives for the executives to behave more aggressively on the product market. A negative β_4 suggests that those firms use less RPE, while in industries with less intense competition (and thus a high $F(H_j)$) firms more often filter out the systematic risks.

The theoretical prediction developed by Aggarwal and Samwick (1999b), claims that the ratio α/β from equation (25) is a decreasing function of the degree of competition. This test is defined as follows:

$$R(\beta) \equiv \frac{\partial(\frac{\alpha}{\beta})}{\partial F(H)} = \frac{\beta_2 \cdot \beta_3 - \beta_1 \cdot \beta_4}{(\beta_2 + \beta_4 \cdot F(H))^2} \tag{27}$$

In presence of a Bertrand competition, the authors expect $R(\beta) > 0$ and in presence of a Cournot competition $R(\beta) < 0$. The compensation ratio test $R(\beta) = 0$ is rejected for all different specifications. More precisely, the results show a positive $R(\beta)$ and thus further support the Bertrand competition model.[7]

[7] The tests are performed at the median industry concentration, i.e. $F(H) = 0.5$.

4.2 CEO-specific characteristics and CEO actions

4.2.1 Personal hedging

Some researchers argue that RPE contracts are not necessary because the executives can personally hedge against systematic risks. The reasoning behind this argument is that the risk exposure and incentives of the executives do not only stem from their compensation contract, but from the overall portfolio they hold, i.e. including privately held assets.

Core et al. (2003) state how a lack of explicit RPE in a compensation scheme does not necessarily imply a lack of implicit RPE in the agent's overall portfolio. They provide a descriptive example by taking the view of a rational, risk-averse CEO, who holds, consistent with the portfolio theory, a well-diversified portfolio with the expected market return R_M. She enters into a new firm, which requires her to hold a certain amount of equity, and sells some of her market portfolio to buy shares of her company. She is now still exposed to the market risk (depending on the beta of the firm, she would have to increase or decrease her holdings in the market portfolio to attain at the same level as before), but additionally also to the idiosyncratic risk of the firm. Core et al. (2003) argue that most incentives for executives come from their equity holdings and not from the annual flow compensation. Thus, this implicit RPE can generate the proper incentives even if there is no explicit RPE in the contract.

One drawback for the empiricists as well as for the board of directors, who designs the compensation package, is that the CEO wealth generally cannot be measured precisely. The principal does therefore not know what the necessary amount of equity holdings is to induce the optimal incentives. If the principal requires too much equity holdings, then the CEO is exposed to a high degree of idiosyncratic risk, which in turn would require a higher risk premium to be paid. In contrast, if the required equity holdings are too low, only weak incentives are provided to the CEO.

On the other hand, if the CEO has outside wealth that she can invest in assets, she might choose a portfolio, where her overall exposure represents again the market portfolio. This can e.g. be done by giving a higher weight to assets with a low correlation to the own firm in order to compensate for the large amount of the firm's own shares that she is forced to hold. As long as it is costless for the CEO to adjust her personal exposure, a RPE contract provides thus no benefits, since any given RPE element in the contract will be offset by personal portfolio adjustments (Maug, 2000).

Garvey and Milbourn (2003) analyze a setting, where executives can hedge the market and where adjusting the manager's exposure to the market risk is costly for both the manager and the firm. The optimal level or RPE depends then on the relative costs of the two players. For example, if the cost to the firm increases relative to the one of the manager, the firm gives a lower RPE-weight and the manager will hedge more privately.

Garvey and Milbourn (2003) empirically test their hypothesis of whether the level of RPE differs with the executive's possibilities to hedge personally and the firm's cost to provide RPE. Since the cost for RPE and private hedging cannot be observed, the following proxies are used. The first proxy for the manger's cost to hedge market risk is her age. An older manager is supposed to have more accumulated financial wealth than a younger and can thus more freely allocate her assets. The authors also estimate individual executive's wealth for a subsample in order to obtain a second, more direct proxy of their wealth.

To capture the costs to the firm in providing RPE, the absolute number of executives leaving their firm within an industry is identified. In industries where CEO turnover is high, the firm is assumed to face higher costs of providing RPE. This is consistent with the literature, such as in Oyer (2004), where the CEO's outside wealth varies with the industry return. In those cases it can be optimal to provide some pay for systematic risk, because otherwise the CEO might leave the firm, which implicates turnover costs.[8]

[8]The effect of CEOs outside options on RPE are further discussed in the next subsec-

Garvey and Milbourn (2003) use a one-step model, where the regression equation takes the following form:

$$\begin{aligned} z_{i,t} &= \beta_0 + \beta_1 \cdot x_{i,t} + \beta_2 \cdot (x_{i,t} \times \mathit{age}) + \beta_3 \cdot (x_{i,t} \times \mathit{mobility}) \\ &\quad +\beta_4 \cdot y_{i,t} + \beta_5 \cdot (y_{i,t} \times \mathit{age}) + \beta_6 \cdot (y_{i,t} \times \mathit{mobility}) \\ &\quad +\beta_7 \cdot C_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{28}$$

The authors measure peer performance $y_{i,t}$ by a firm-specific CAPM-based benchmark and, in an alternative specification, by the S&P500 index. The variables *age* and *mobility* are computed by the value of the respective cumulative distribution function (cdf).[9]

In a first step, the authors do not include the variables *age* and *mobility* and only use $x_{i,t}$, $y_{i,t}$ and the control variables. They perform a typical weak-form RPE test by looking whether the coefficient on $y_{i,t}$ is negative. This estimate is however not significant and thus confirms the lack of RPE.

Next, Garvey and Milbourn (2003) test the main hypothesis of their study, namely whether $\beta_5 > 0$ and $\beta_6 > 0$. Using the S&P500 as peer index, the authors obtain the following results. The coefficient β_4 is significantly negative and β_5 is significantly positive. This provides evidence that RPE is more present for young CEOs than for older ones. For example, the variable *age* takes the value zero for the youngest CEO and thus $\beta_5 \cdot \mathit{age} = 0$. Since β_4 is negative, firms filter out market risks at least partially for young CEOs. In contrast, for the oldest CEO the variable *age* takes the value one and thus $\beta_5 \cdot \mathit{age} > 0$. This neutralizes the negative coefficient β_4 and therefore, no evidence of RPE is found for the oldest CEO. The results persists for the second proxy, a direct estimate of wealth for a subsample of CEOs.

tion.

[9]Garvey and Milbourn (2003) also include variables for the systematic and idiosyncratic variance of the firm and interact them with $x_{i,t}$, $x_{i,t} \times \mathit{age}$ and $x_{i,t} \times \mathit{mobility}$ (I do not include them in the equation above for reasons of readability and because I do not interpret these coefficients).

In terms of the CEO mobility, Garvey and Milbourn (2003) find no support for their hypothesis that a high CEO mobility is associated with a lower degree of RPE. The estimate β_6 is close to zero and not significantly positive, which the authors expect to find if the costs for providing RPE would be high in industries with more CEO turnovers.

4.2.2 CEO outside options

Oyer (2004) views bonus schemes, such as stock option plans, not only as instrument to incentivize the executives, but also to index wages to the current market situation. The basic assumption behind this reasoning is that the executive's outside options vary with the market conditions. This is a deviation from the standard principal-agent setting, where the reservation utility is exogenously given. A certain pay for market risks is optimal if the executive's outside options depend on the market conditions, because in good times, the outside options increase and the contract has to be adjusted in order to retain the manager. Tying the pay to the market situation automatically makes this adjustment.

The principal might instead also write a new contract in every period in which he considers the changes in the market situation. However, Oyer (2004) introduces a second important assumption in his model, which is that turnover and adjustments in the contract parameters are costly, which in turn makes replacing the manager or continuous recontracting less attractive to the principal.

Rajgopal et al. (2006) empirically test whether CEOs with better outside opportunities are compensated for market risk. Since CEOs' outside options are not observable, the authors hypothesize that CEO talent does as well reflect her outside opportunities and that in economic booms there is a higher demand for talented CEOs. While it seems obvious that more qualified CEOs have better outside options, the assumption that their demand is higher in prosperous economic times can certainly be questioned. The reasoning of the authors, which follows Oyer (2004), is that e.g. a booming industry attracts possible new competitors or rival firms start new projects, and managerial talent is thus needed to cope with this situation.

However, one might as well think that especially in difficult times a highly skilled CEO is necessary to lead the firm. The authors acknowledge this view and test also for asymmetries in RPE, i.e. whether the talented CEOs are protected from economic downturns.

A second difficulty in implementing this empirical test is to find a valid proxy for CEO talent. Rajgopal et al. (2006) do this by counting the positive press articles on CEOs and by computing industry-adjusted average ROA. A high number of positive press citations and outperforming the industry ROA are taken as signs for superior CEO talent. The results do not differ much whatever proxy is used. This gives some support for the proxies, but of course, the inherent difficulty to measure a CEO's talent cannot be overridden. The main regression takes then the following form:

$$\begin{aligned} z_{i,t} &= \beta_0 + \beta_1 \cdot x_{i,t} + \beta_2 \cdot y_{i,t} + \beta_3 \cdot (y_{i,t} \times talent_{i,t}) \\ &\quad + \beta_4 \cdot (x_{i,t} \times C_{i,t}) + SIC_i + Y_t + \epsilon_{i,t} \end{aligned} \tag{29}$$

The peer performance $y_{i,t}$ takes the form of an industry and a market index, respectively. The variable $talent_{i,t}$ is computed as the value of the empirical cumulative distribution function (cdf) of the CEO talent proxies described above. The authors add control variables to the regression (firm size, CEO tenure, CEO age and the firm's equity return variance), as well as industry and year fixed effects.

The structure of the regression model is very similar to the other approaches described so far. It takes basically the form of a weak-form RPE test, but additionally includes an interaction of $y_{i,t}$ and another variable to investigate whether this other variable affects the extent of RPE.

Rajgopal et al. (2006) thus first test for the presence of weak-form RPE by the hypothesis $\beta_2 < 0$ and then investigate their main hypothesis $\beta_3 > 0$. The estimate β_2 is negative and significant, which supports the presence of weak-form RPE. The next test then clarifies whether this results holds for all CEOs or whether it differs with the CEO's talent. The regression results present some evidence that the level of RPE is indeed lower for talented CEOs. The coefficient β_3 is positive and significant, which means that the industry or market risk is filtered out for least talented CEOs, but not for the most talented ones.

The main results are however only statistically significant at the 10%-level using a one-tailed test. Additionally, the magnitude of the coefficients β_2 and β_3 are very low compared to β_1.[10] For example, the coefficients of a median regression using the model (29) are $\beta_1 = 15.82$, $\beta_2 = -2.36$, $\beta_3 = 0.77$ if the authors use the number of press articles as proxy for CEO talent and $\beta_3 = 0.55$ if they use the industry-adjusted ROA.

4.3 RPE and the managerial power approach

The managerial power approach has received considerable attention in the executive compensation literature and has been discussed under several terms, e.g. skimming (Bertrand and Mullainathan, 2001), rent seeking/extraction (Bebchuk et al., 2002) or simply named as excessive pay (Bebchuk and Fried, 2003). The managerial power approach assumes that the agent has some power over the pay-setting process, which she uses to extract a rent at the expense of the shareholders. Some possible arguments for this assumption are that the manager has influence over the appointment of the directors, the manager can hire compensation consultants to justify her salary or other effects, which are generally the outcome of deficiencies in the firm's corporate governance (Bebchuk et al., 2002).

As in the sections before, the advantages of RPE are generally acknowledged

[10]Rajgopal et al. (2006) accordingly clearly reject the strong-form test $\beta_1 + \beta_2 = 0$ in their study.

in those papers, but now the shortcomings arise from the agent's power over the pay-setting process and not from the CEO's hedging possibilities or outside options. Correctly implemented, RPE would provide a good tool to increase the efficiency of compensation contracts and taking measures like improving a firm's corporate governance can lead to lower managerial power and increased use of RPE (Bebchuk et al., 2002).

One might wonder why a risk-averse CEO, who has power over the pay-setting process, would chose to increase her risky variable compensation instead of the predetermined, fixed salary. There exists a well-established reason for this behavior. The ability of a CEO to increase her pay level is limited, even for very powerful CEOs. At a certain level, the board of directors, the shareholders and the general public would notice and suppress the rent seeking behavior. With this limitation in mind, a CEO seeks to camouflage the high pay level (see e.g. Bertrand and Mullainathan (2001) or Bebchuk et al. (2002)). The absence of RPE, respectively the presence of pay for luck, is a possibility to hide the rent extraction.

4.3.1 Failures in corporate governance

Bertrand and Mullainathan (2001) investigate how weaknesses in corporate governance affect the presence of reward for luck.[11] Their RFL test is more general than a typical RPE test. It investigates for different (observable) luck factors, whether they are filtered out from the CEO's compensation, whereas the typical RPE test uses an index or a peer group performance to investigate whether the firms filters out (unobservable) common shocks from the manager's remuneration.

More precisely, the study from Bertrand and Mullainathan (2001) uses three different measures for luck, namely oil prices, exchange rates and industry

[11] The authors use the term reward for luck (RFL) rather than RPE. However, both terms basically describe the same concept, where the presence of reward for luck can be described as absence of RPE. The empirical approach is the same in both cases and thus, I discuss the RFL test in this survey in the same way as any RPE test.

performance. The latter corresponds to a typical RPE test and shows that the notions of RPE and RFL are not clearly delimited in the literature. Bertrand and Mullainathan (2001) use the industry performance as luck measure to present their main results.

The authors use a typical strong-form test in their study. In a first step, the performance measure $x_{i,t}$, measured as logarithmic shareholder returns, is regressed on the luck variable:

$$x_{i,t} = \gamma_0 + \gamma_1 \cdot y_{i,t} + \gamma_2 \cdot C_{i,t} + F_i + Y_t + \varepsilon_{i,t} \tag{30}$$

$y_{i,t}$ is the observable luck variable (oil price, exchange rate index, or industry performance), $C_{i,t}$ are the control variables (CEO tenure, CEO age), F_i and Y_t are firm and year fixed effects, respectively. Using the results of this equation, the authors predict the part of the firm performance which is due to luck, and define this systematic risk component as $x^s_{i,t} = \hat{\gamma}_1 \cdot y_{i,t}$. The RFL-test then takes the form

$$z_{i,t} = \beta_0 + \beta_1 \cdot x^s_{i,t} + \beta_2 \cdot C_{i,t} + F_i + Y_t + \varepsilon_{i,t} \tag{31}$$

and tests the hypothesis $\beta_1 = 0$, which is what one would expect if observable luck is completely filtered out. The difference between the strong-form test described in section 3.1 is that the firm performance itself is not included in the regression. This does however not affect the expectation for β_1 in any way.

The strong-form RPE hypothesis is rejected for all three kind of luck variables at the 5%-level. Bertrand and Mullainathan (2001) also compute the regression (31) with $x_{i,t}$ as independent variable (instead of $x^s_{i,t}$) to show that there is a positive pay-performance sensitivity for $x_{i,t}$ in general, and to compare it to the pay-for-luck sensitivity. The regression coefficient for the general pay-performance sensitivity is named $\beta^{General}$ and the one for the pay-for-luck sensitivity β^{Luck}. The differences between these two estimates is not significant, meaning that CEO pay responds as much to a 'lucky' dollar as to a 'general' dollar (Bertrand and Mullainathan, 2001).

The main hypothesis is then investigated in a next step. In order to test whether the CEO has captured the pay-setting process, the Bertrand and Mullainathan (2001) include a measure for corporate governance in the regression. Since in poorly governed firms it is easier for CEOs to gain control on the pay-setting process, the authors expect more pay for luck in those firms compared to the ones with a good corporate governance.

Bertrand and Mullainathan (2001) use the presence of a large shareholder (holding at least 5% of the firm's common shares) as proxy for governance, assuming that such an investor has greater incentives to watch over the firm than a group of dispersed shareholders. The corresponding variable Gov is thus binary and takes the value one if the firm has a large shareholder. Alternatively, the authors use board size (where a small board is assumed to be more effective) and the fraction of insiders on the board (many insiders are assumed to weaken the governance) to proxy for governance. The regression model takes the following form:

$$z_{i,t} = \beta_0 + \beta_1^{Luck} \cdot x_{i,t}^s + \beta_2^{Luck} \cdot (Gov_{i,t} \times x_{i,t}^s) + \beta_3 \cdot C_{i,t} + \beta_4 \cdot Gov_{i,t} + F_i + Y_t + \varepsilon_{i,t} \tag{32}$$

The estimated coefficient $\hat{\beta}_2^{Luck}$ measures the effect of governance on pay for luck, i.e. a positive (negative) coefficient means that firms with a good corporate governance are more (less) sensitive to pay for luck. As before, the same regression is also run with $x_{i,t}$ as independent variable (instead of $x_{i,t}^s$) and the estimated effect of governance on the general pay sensitivity is $\hat{\beta}_2^{General}$ (instead of $\hat{\beta}_2^{Luck}$). The test then consists of comparing $\hat{\beta}_2^{General}$ and $\hat{\beta}_2^{Luck}$.

The results show again that there is a significant sensitivity to a general dollar as well as to a lucky dollar ($\beta_1^{General}$ and β_1^{Luck} are both significantly positive). However, adding a large shareholder does not significantly reduce the sensitivity to a general dollar ($\beta_2^{General}$ cannot be distinguished from zero), whereas the decrease in the sensitivity to a lucky dollar ($\beta_2^{Luck} < 0$) is significant. The effect is the strongest when the presence of a large shareholder is used as proxy for good governance. This supports the hypothesis that there is less RFL in firms with good corporate governance.

4.3.2 Asymmetric RPE

A point, which Bertrand and Mullainathan (2001) only marginally address, is a potential asymmetry in RPE.[12] If a CEO really can influence her pay level, she would only want a RPE based compensation if it is in her interest, i.e. if the peer performance was bad. Garvey and Milbourn (2006) investigate this possible asymmetry in RPE. They assume that a compensation package is not completely determined ex ante, but that the board of directors decides on some parts of variable pay at the end of a period. At this point it is known whether the firm has outperformed the industry or not, and the manager uses her influence over the board to implement RPE (if the industry performance was bad) or not (if the industry performance was good).

The authors use a two-step approach similar to Bertrand and Mullainathan (2001) in order to separate the 'luck' component in a firm's performance from the 'skill' component. The first step consists of regressing the firm performance on an equal-weighted industry index ($y_{i,t}^{ew}$) and a value-weighted industry index ($y_{i,t}^{vw}$):

$$x_{i,t} = \gamma_0 + \gamma_1 \cdot y_{i,t}^{ew} + \gamma_2 \cdot y_{i,t}^{vw} + Y_t + u_{i,t} \tag{33}$$

The approach to include two benchmarks instead of just one is different from most other RPE studies. Furthermore, the two chosen benchmarks are very similar. In both cases, the 2-digit SIC code is used to create the industry index and the only difference is the aggregation rule. The exact benefits of using both indices instead of just one remain unclear. However, Garvey and Milbourn (2006) also use other peer and luck measures and find that their

[12] Some anecdotal evidence for asymmetric pay for luck is provided on the oil industry by showing a graphical analysis (figure 3 in their paper).

main results are robust to those different specifications.

The luck variable for the second step regression is defined as $x^s_{i,t} = \hat{\gamma}_0 + \hat{\gamma}_1 \cdot y^{ew}_{i,t} + \hat{\gamma}_2 \cdot y^{vw}_{i,t} + \hat{Y}_t$ and the skill variable is accordingly $x^u_{i,t} = \hat{u}_{i,t}$, i.e. the idiosyncratic performance shock represents skill. The second step regression is thus estimated by the following model:[13]

$$z_{i,t} = \beta_0 + \beta_1 \cdot x^u_{i,t} + \beta_2 \cdot x^s_{i,t} + \beta_5 \cdot C_{i,t} + F_i + Y_t + \varepsilon_{i,t} \tag{34}$$

Both coefficients β_1 and β_2 are significantly positive, the latter confirming the presence of reward for luck and the absence of RPE, respectively. The RPE test $\beta_2 = 0$ is thus rejected and Garvey and Milbourn (2006) can address their main research question, i.e. whether the pay for luck is more pronounced if luck is positive compared to when it is negative. The authors add dummy variables to the regression model (34), where the dummy equals one if luck (skill) is negative and zero otherwise. The dummy is then interacted with the luck (skill) variable, which gives the following regression model:

$$\begin{aligned} z_{i,t} = {} & \beta_0 + \beta_1 \cdot x^u_{i,t} + \beta_2 \cdot (x^u_{i,t} \times D^u) + \beta_3 \cdot x^s_{i,t} + \beta_4 \cdot (x^s_{i,t} \times D^s) \\ & + \beta_7 \cdot C_{i,t} + F_i + Y_t + \varepsilon_{i,t} \end{aligned} \tag{35}$$

The skimming hypothesis tests whether $\beta_4 < 0$ and $\beta_2 = \beta_4$. A negative β_4 suggests that the industry performance is filtered out if it is negative. It is however possible in an optimal contract to obtain the result $\beta_4 < 0$ if at the same time one observes $\beta_2 = \beta_4$. In this case, the 'punishment' for bad luck is equal to the one for bad skill, which is not what one would observe if the executive has captured the pay process.

The estimate for $\beta_4 < 0$ is negative and significant. This result provides evidence for the asymmetry in RPE, because there appears to be no filtering if the industry return is positive (β_3 is still positive and significant), but at

[13] The authors also include the cdf of the variances of $x^s_{i,t}$ and $x^u_{i,t}$ in their strong-form test. I do not show them in the equation (34) for reasons of readability and because I do not interpret these coefficients.

least some filtering if the industry return is negative.[14] Second, Garvey and Milbourn (2006) reject $\beta_2 - \beta_4 = 0$, which further supports the skimming hypothesis.

5 Conclusion

This study provides a summary on the methodology of empirical RPE tests and their explanations of the RPE puzzle. In a first step, I explained how researchers generally conduct strong-form and weak-form tests. Because the numerous RPE tests so far have not found clear evidence in favor of RPE, the researchers have been looking for different explanations why RPE might be harmful for some firms or why it might be optimal, but rarely implemented. In a second step, I thus described the prevalent explanations for the RPE puzzle in terms of their methodology and results.

I classified the selected studies for this survey in the categories strategic considerations, CEO characteristics and the managerial power approach. This approach is of course only one of many possibilities to give a clear view on the academic RPE literature, but in my view these are categories which have been investigated profoundly and which are able to capture the most prevailing pros and cons of RPE. The categorization also helps to explain the differences in the empirical methodologies and to compare the different studies with each other.

The empirical approach of most studies to explain the lack of RPE is very similar. The researchers confirm in a first step the absence of RPE in order to establish a basis for their further analysis. In a second step, the researchers investigate their explanation for the absence of RPE by introducing their variable of interest in the regression. They test whether the extent of RPE varies with respect to changes in the variable of interest. For example, Bertrand

[14] The magnitude of the estimate β_4 is low compared to β_3. Taken together, the executive pay is still sensitive to industry returns, even if they are negative. The executives are thus not completely shielded from bad luck.

and Mullainathan (2001) test whether the extent of RPE is different for firms with weak or strong corporate governance.

The majority of the studies summarized in this paper find empirical support for their explanation of the RPE puzzle (see Appendix A for an overview of the empirical approach and the main findings for each RPE study discussed in this survey). However, there seems to be no explanation which consistently provides stronger evidence than the others. Thus, there are multiple explanations why a limited use of RPE can be optimal for executives and shareholders. For a researcher it is important to know about these different aspects in order to better understand the use of RPE in the context of executive compensation. This survey can help to take a look at the RPE puzzle from different points of view and to deal with the proposed solutions in a critical and differentiated way.

There is evidence suggesting that the number of firms using RPE has increased during the last years, which shows that the topic is still relevant these days (Bettis et al., 2014).[15] The reason for this increase remains however unclear. Do firms only learn now about the benefits of RPE? Have improvements in corporate governance led to a wider dispersal of RPE? Are the firms under pressure (e.g. from shareholder activists, proxy advisors, media or political forces) to use RPE even though they think it would not be useful for their firm? Further research might use the information of a firm's decision to implement or discontinue RPE contracts in order to find support for or against the existing explanations or even provide completely new insights on the RPE puzzle.

[15]Bettis et al. (2014) report data on RPE usage from 1998 to 2012, with 386 firms out of 1149 using RPE in 2014 (33.6%), compared to 16.8% in 2006 and 5.5% in 1998.

Appendix A: Overview on empirical RPE studies

Study	peer group composition	peer group aggregation	alternative RPE explanation	result
Aggarwal and Samwick (1999b)	industry (SIC4)	value-weighted	strategic considerations	Y[1]
Antle and Smith (1986)	industry (SIC2)	correlation-based	-	N[2]
Bertrand and Mullainathan (2001)	oil price, FX rates, industry(SIC2)	value-weighted	weak corporate governance	Y
Garvey and Milbourn (2003)	S&P500	-	personal hedging	Y[3]
Garvey and Milbourn (2006)	industry (SIC2)	equal-weighted, value-weighted	asymmetric RPE	Y
Gibbons and Murphy (1990)	industry (SIC2)	value-weighted	-	Y[4]
Gong et al. (2011)	disclosed peers	median value	-	Y
Rajgopal et al. (2006)	industry (SIC2)	value-weighted	outside options	Y

The table provides an overview of the empirical RPE tests that I discussed in the present survey. It enlarges the existing overviews in Albuquerque (2009) or Dikolli et al. (2013) by adding the study's explanation for the RPE puzzle in the column 'alternative RPE explanation' and whether the study has found evidence in favor of their alternative hypothesis. Appendix 5 presents further details on the empirical approach of each study.
N = no evidence found in favor of the alternative RPE explanation.
Y = data supports the alternative RPE explanation.
[1] Y for Bertrand model, N for Cournot model.
[2] N for strong- and weak-form RPE.
[3] Y *age* is used as proxy for personal hedging, N if *mobility* is used as proxy for personal hedging.
[4] Y for the presence of weak-form RPE.

Appendix B: Overview on the empirical approach of the RPE studies

Aggarwal and Samwick (1999b)	
alternative hypothesis (H_A)	strategic considerations
regression model	$z_{i,j,t} = \beta_0 + \beta_1 \cdot x_{j,t} + \beta_2 \cdot y_{j,t}$ $+\beta_3 \cdot F(H_j) \times x_{j,t} + \beta_4 \cdot F(H_j) \times y_{j,t}$ $+\beta_5 \cdot F(H_j) + \beta_6 \cdot CEO_{i,t} + SIC_j + Y_t + \varepsilon_{i,j,t}$
firm performance x	shareholder return
peer group	industry (SIC3 and SIC4)
aggregation rule	value-weighted
control variables	CEO, industry + year FE
RPE test	$\beta_2 + \beta_4 \cdot F(H_j) < 0$ (weak-form)
result	N
test for H_A	$R(\beta) = \dfrac{\beta_2 \cdot \beta_3 - \beta_1 \cdot \beta_4}{(\beta_2 + \beta_4 \cdot F(H))^2} = 0$
result	Y for Bertrand model, N for Cournot model

N = hypothesis rejected.
Y = hypothesis is not rejected, data supports the presence of RPE or the alternative explanation, respectively.

Antle and Smith (1986)	
alternative hypothesis (H_A)	-
regression model[1]	$z_{i,t} = \beta_0 + \beta_1 \cdot x^u_{i,t} + \beta_2 \cdot x^s_{i,t} + \varepsilon_{i,t}$
firm performance x	RET, ROA
peer group	industry (SIC2)
aggregation rule	correlation-weighted
control variables	-
RPE test	$\beta_1 \neq \beta_2$ (weak-form)
	$\beta_2 = 0$ and $\beta_1 > \beta_2$ (strong-form)
result	N[2] (weak-form)
	N[3] (strong-form)
test for H_A	-
result	-

N = hypothesis rejected.
Y = hypothesis is not rejected, data supports the presence of RPE or the alternative explanation, respectively.
[1] Two-step approach applied. The table shows the second step regression only.
[2] Y only for 7(6) out of 39 firms in RET(ROA) (5%-level).
[3] Y only for 2(6) out of 39 firms in RET(ROA) (5%-level).

Bertrand and Mullainathan (2001)	
alternative hypothesis (H_A)	weak corporate governance
regression model[1,2]	$z_{i,t} = \beta_0 + \beta_1^{Luck} \cdot x^s_{i,t} + \beta_2^{Luck} \cdot (Gov_{i,t} \times x^s_{i,t})$
	$+\beta_3 \cdot C_{i,t} + \beta_4 \cdot Gov_{i,t} + F_i + Y_t + \varepsilon_{i,t}$
firm performance x	shareholder return,
	accounting return (income/assets)
peer group	oil price, FX exchange rates, industry (SIC2)
aggregation rule	value-weighted (for industry peer group)
control variables	CEO age, CEO tenure, firm + year FE
RPE test[3]	$\beta_1^{Luck} = 0$
result	N (for oil prices, FX rates, industry return)
test for H_A	$\beta_2^{Luck} \neq \beta_2^{General}$
result	Y ($\beta_2^{Luck} < \beta_2^{General}$)

N = hypothesis rejected.
Y = hypothesis is not rejected, data supports the presence of RPE or the alternative explanation, respectively.
[1] Two-step approach applied. The table shows the second step regression only.
[2] The compensation $z_{i,t}$ is also regressed on the overall performance $x_{i,t}$, i.e. $z_{i,t} = \beta_0 + \beta_1^{General} \cdot x_{i,t} + \beta_2^{General} \cdot (Gov_{i,t} \times x_{i,t}) + \beta_3 \cdot C_{i,t} + \beta_4 \cdot Gov_{i,t} + F_i + Y_t + \varepsilon_{i,t}$
[3] For this test, the variable $Gov_{i,t}$ is not yet included in the regression.

Garvey and Milbourn (2003)	
alternative hypothesis (H_A)	personal hedging
regression model	$z_{i,t} = \beta_0 + \beta_1 \cdot x_{i,t} + \beta_2 \cdot (x_{i,t} \times \mathit{age})$
	$+\beta_3 \cdot (x_{i,t} \times \mathit{mobility}) + \beta_4 \cdot y_{i,t}$
	$+\beta_5 \cdot (y_{i,t} \times \mathit{age}) + \beta_6 \cdot (y_{i,t} \times \mathit{mobility})$
	$+\beta_7 \cdot C_{i,t} + \mathit{SIC}_i + Y_t + \varepsilon_{i,t}$
firm performance x	shareholder return
peer group	CAPM benchmark[1], S&P500
aggregation rule	-
control variables	firm-specific and systematic variance,
	Tobin's q, industry + year FE
RPE test	$\beta_4 < 0$ (weak-form)
results	Y[1]
test for H_A	$\beta_5 > 0$, $\beta_6 > 0$
results	Y for *age* (β_5), N for *mobility* (β_6)

N = hypothesis rejected.
Y = hypothesis is not rejected, data supports the presence of RPE or the alternative explanation, respectively.
[1] The CAPM benchmark is a firm-specific return consisting of the risk-free return and an estimated beta times the realized premium of the S&P500 return over the risk-free rate.
[1] N if the variables $(y_{i,t} \times \mathit{age})$ and $(y_{i,t} \times \mathit{mobility})$ are excluded from the regression.

Garvey and Milbourn (2006)	
alternative hypothesis (H_A)	asymmetric RPE
regression model[1]	$z_{i,t} = \beta_0 + \beta_1 \cdot x^u_{i,t} + \beta_2 \cdot (x^u_{i,t} \times D^u) + \beta_3 \cdot x^s_{i,t}$ $+\beta_4 \cdot (x^s_{i,t} \times D^s) + \beta_7 \cdot C_{i,t} + F_i + Y_t + \varepsilon_{i,t}$
firm performance x	stock returns
peer group	industry (SIC2)
aggregation rule	equal- and value-weighted
	(both included in the first step regression)
control variables	CEO tenure, $\mathrm{Var}(x^s_{i,t})$, $\mathrm{Var}(x^u_{i,t})$, firm + year FE
RPE test[2]	$\beta_3 = 0$ (strong-form)
result	N
test for H_A	$\beta_4 < 0$ and $\beta_2 = \beta_4$ (weak form)
result	Y

N = hypothesis rejected.
Y = hypothesis is not rejected, data supports the presence of RPE or the alternative explanation, respectively.
[1] Two-step approach applied. The table shows the second step regression only.
[2] For this test, the variables $(x^u_{i,t} \times D^u)$ and $(x^s_{i,t} \times D^s)$ are excluded from the regression.

Gibbons and Murphy (1990)	
alternative hypothesis (H_A)	-
regression model	$z_{i,t} = \alpha_0 + \alpha_1 \cdot x_{i,t} + \alpha_2 \cdot y_{i,t} + \varepsilon_{i,t}$
firm performance x	stock return
peer group	industry (SIC2), market
aggregation rule	value-weighted
control variables	-
RPE test	$\alpha_2 < 0$ (weak-form)
result	Y (for both industry and market benchmark)
test for H_A	-
result	-

N = hypothesis rejected.
Y = hypothesis is not rejected, data supports the presence of RPE or the alternative explanation, respectively.

Gong et al. (2011)	
alternative hypothesis (H_A)	-
regression model	$z_{i,t} = \alpha_0 + \alpha_1 \cdot x_{i,t} + \alpha_2 \cdot y_{i,t} + \alpha_c \cdot C_{i,t} + \varepsilon_{i,t}$
firm performance x	stock return
peer group	industry-size, disclosed peer group
aggregation rule	median stock return
control variables	firm size, growth options, CEO tenure, idiosyncratic variance, CEO is board chair, CEO stock ownership, industry FE
RPE test	$\alpha_2 < 0$ (weak-form)
result	N for industry-size, Y for disclosed peer group
test for H_A	-
result	-

N = hypothesis rejected.
Y = hypothesis is not rejected, data supports the presence of RPE or the alternative explanation, respectively.

Rajgopal et al. (2006)	
alternative hypothesis (H_A)	CEO outside options
regression model	$z_{i,t} = \beta_0 + \beta_1 \cdot x_{i,t} + \beta_2 \cdot y_{i,t}$
	$+\beta_3 \cdot (y_{i,t} \times talent_{i,t}) + \beta_4 \cdot (x_{i,t} \times C_{i,t})$
	$+SIC_i + Y_t + \epsilon_{i,t}$
firm performance x	shareholder return
peer group	industry (SIC2)
aggregation rule	value-weighted
control variables	CEO tenure, CEO age, firm size
	Var(x), industry + year FE
RPE test	$\beta_2 < 0$ (weak-form)
	$\beta_1 + \beta_2 = 0$ (strong-form)
result	Y for weak-form RPE, N for strong-form RPE
test for H_A	$\beta_3 > 0$
result	Y[1]

N = hypothesis rejected.
Y = hypothesis is not rejected, data supports the presence of RPE or the alternative explanation, respectively.
[1] for both talent proxies (number of positive press articles on the CEO and outperforming the industry-adjusted ROA).

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Peer group composition and aggregation for RPE purposes in presence of exposure risk

Abstract

Agency theory suggests the use relative performance evaluation (RPE) to filter out systematic risks from a noisy performance measure. The presence of exposure risk, i.e. if the exposure to the systematic risks moves over time, however precludes complete filtering. In the present study I first estimate the exposure of a firm's performance to the performance of potential peer firms in order to construct a firm-specific peer group. Second, I investigate how the presence of exposure risk can affect the composition and aggregation of a peer group over time. Third, I show how these movements in the peer group composition and aggregation can reduce the effectiveness of the filtering purpose in RPE settings. I find that the firm-specific peer groups provide good filtering abilities ex post, but that simple indices, such as industry peer groups, are more stable and thus perform better out-of-sample.

1 Introduction

According to the agency theory, relative performance evaluation (RPE) is a useful way to make an agent's compensation more efficient. While rewarding the agent for absolute firm performance aligns her personal goals with those of the shareholders and thus creates incentives to act in the interest of the shareholders, the purpose of RPE is to filter out systematic risks from a noisy firm performance. This permits a variance reduction in the compensation of the risk-averse agent without reducing her incentives, which increases the overall efficiency of the contract.

Empirical research on RPE has mostly focused on investigating whether or not firms actually use RPE as predicted by the agency theory, but the results so far are mixed. The missing empirical evidence in support of RPE has led to the situation known as the RPE puzzle. There have been many attempts to resolve this puzzle. For example Bebchuk et al. (2002) or Bertrand and Mullainathan (2001) explain the lack of RPE as failure in corporate governance. Other authors argue that it can be optimal not to do RPE due to strategic considerations (e.g. Aggarwal and Samwick (1999a) and Gopalan et al. (2010)), CEO hedging possibilities (Garvey and Milbourn, 2003) or CEO outside options (Rajgopal et al., 2006). Some researchers also argue that firms might use RPE, but that the existing empirical approaches have so far been unable to detect it (see e.g. Albuquerque (2009), Gong et al. (2011) or Dikolli et al. (2013)).

One possible explanation for the RPE puzzle is the presence of exposure risk as modeled in Göx (2016). In this view, the exposure to common risks, which are supposed to be filtered out by RPE, is assumed to be a random factor rather than a known constant. The uncertainty about the exposure prevents a perfect filtering of the systematic risks and thus makes RPE less useful. In the present study, I focus on this aspect and investigate how the presence of exposure risk can affect the composition and weighting of a peer group. This investigation is interesting and important for several reasons.

First, the notion of exposure risk in the context of RPE has emerged only recently and, to my knowledge, so far never been empirically investigated. Nevertheless, there is much evidence that the exposure to systematic risks varies over time. For example, Ang and Chen (2007) or Lewellen and Nagel (2006) observe moving beta factors in asset pricing models. Other examples are Bodnar and Wong (2003) or Parsley and Popper (2006), who observe time-varying exchange rate exposures. It is thus important to understand the temporal aspect of those risks and how it affects the filtering purpose of RPE. Second, finding evidence that exposure risk mitigates the usefulness of RPE can provide an additional explanation for the RPE puzzle and support the point of view that such contracts might not necessarily be optimal in any case.

I will take the view of a firm trying to implement an efficient contract and derive my research questions from this point. The first question to address is how a firm can estimate the exposure of its own performance to the one of a set of possible peer firms and use this information to construct a peer index as a performance measure. This index contains a certain number of peer firms and gives each firm a weight, such that the overall variance of the performance measure is minimized. The second question addressed in this study, is how the composition and aggregation of the peer group varies over time. Third, I use the information from the second step to evaluate how well external risks can actually be filtered out by using historical data.

For the first question I rely on existing theoretical models to measure a firm's exposure to its peer firms by OLS regressions. On the basis of these results, I construct a firm-specific peer group. Second, I measure the time-variation in the exposure by means of a rolling regression to determine the exposure risk. Third, I assess how the time-variation affects the composition of the peer group and the filtering purpose of RPE. To do so, I measure by how much the variance can be reduced if the filtering process is applied. I also investigate whether the effectiveness of filtering can be explained by certain characteristics, such as the peer group size or the share of peer firms which belong to the same industry as the focal firm.

My main findings are that the firm-specific peer groups provide good filtering results ex post, but perform much worse out-of-sample. In contrast, simple indices, such as industry peer groups or the S&P500, exhibit a lower filtering effectiveness ex post (compared to the firm-specific peer groups), but a higher one on an out-of-sample basis. Among the self-selected peer groups, a high exposure risk is related to a lower filtering effectiveness.

The study contributes to the literature by providing empirical evidence on the time-varying nature of peer group composition and aggregation and how this affects the usefulness of RPE in terms of risk filtering.

The reminder of the paper is organized as follows. The next section provides a brief literature overview of RPE and time-varying risk exposures, section 3 explains the empirical methodology and section 4 describes the data used for this study. I present the main results in section 5 and robustness checks in section 6. Section 7 summarizes and concludes the study.

2 Related literature

2.1 Relative performance evaluation

RPE is a branch of the academic literature on executive compensation that has intensely been investigated. The theoretical foundation goes back to Holmström (1979), who established the use of informative signals for efficient contracting in a principal agent setting. In a later work, Holmström (1982) describes how different agents, which all belong to a team and are exposed to a common risk, should be rewarded based on the performance relative to the other agents in the team.

Those papers have given rise to a large number of empirical studies on RPE.

Early studies in this field are e.g. Antle and Smith (1986), Gibbons and Murphy (1990), Janakiraman et al. (1992), Aggarwal and Samwick (1999a) or Aggarwal and Samwick (1999b). Despite the clear theoretical prediction, empirical research has only found limited support for the use of RPE in the data. This apparent contradiction between theory and practices has become known as the RPE puzzle.[16]

Among the most prevalent explanations for the observed lack of RPE is the managerial power approach. In this view, managers have power over the pay-setting process and thus prevent the implementation of RPE or allow only asymmetric RPE (see e.g. Bertrand and Mullainathan (2001), Bebchuk et al. (2002), Garvey and Milbourn (2006) or Jiménez-Angueira and Stuart (2015)). The managerial power approach acknowledges the benefits of RPE and argues that it is mainly due to failures in the firm's corporate governance that RPE contracts are not set in place.

Other approaches suggest that it can be optimal not to do RPE, for example because the manager can affect the peer outcome (as in Gibbons and Murphy (1990) or Gopalan et al. (2010)) or because it creates incentives for harmful strategic considerations (as e.g. in Aggarwal and Samwick (1999b)). A further explanation is that the optimal extend to which RPE is provided to an agent depends on her characteristics or actions, such as the ability to hedge the market (see e.g. Maug (2000) or Garvey and Milbourn (2003)) or the agent's outside options (as e.g. in Oyer (2004), Rajgopal et al. (2006) or Jenter and Kanaan (2015)).

A different approach for explaining the RPE puzzle is provided amongst others by Albuquerque (2009), Gong et al. (2011) or Dikolli et al. (2013). In those cases, the authors claim that RPE might be done by the firms but simply not detected by researchers. Dikolli et al. (2013) analytically investigate the summarization errors which occur because the empiricists

[16] Summaries on the empirical findings of RPE tests can be found in Albuquerque (2009) and Dikolli et al. (2013), where an overview of the test form (weak-, or strong-form test), the used peer group and the results is provided.

cannot observe the composition and the aggregation rule of the peer group, i.e. the weight assigned to the single peers within the group. Those errors can lead to wrong inferences in RPE tests and show how sensitive these results are to changes in the peer group identification or aggregation.

While most RPE tests use an industry or market index as peer group, Albuquerque (2009) matches the peer firms not only on industry, but as well on size. Those industry-size peer groups are then shown to find more consistent evidence for the presence RPE compared to the industry only peer group.

Gong et al. (2011) use the information from SEC disclosure rules which came into force in 2006 and required the firms to disclose the peers used for compensation benchmarking or RPE. The authors were thus able to first conduct an explicit RPE test and empirically show how the traditional implicit approach has led to possibly wrong inferences. More precisely, Gong et al. (2011) incorporate the disclosed peer group composition in their test and find strong support for RPE.[17]

Furthermore, Gong et al. (2011) conduct a RPE test by using a sample of firms, which all explicitly disclose their use of RPE. But instead of regressing the focal firm's performance on the disclosed, self-selected peer group, the authors take a simplified peer group composition, such as industry or industry-size peers. In this case, no significant results can be found in favor of RPE. This shows the limitations of the implicit RPE tests and emphasize the importance of the composition of the peer group in such tests.

2.2 Exposure risk in RPE

The effect of random exposures to common risks has been largely ignored so far in the academic literature on RPE. The prevailing assumption is that all

[17]However, there is still some uncertainty left to the empiricists, since the weighting of the single peer firms within the group is not disclosed, as already pointed out by Dikolli et al. (2013).

firms exactly know how their performance reacts to external shocks, i.e. what their exposure is, and thus are able to completely filter out those shocks. One can however easily imagine why this may not be the case. For example, one can think of a firm which is exposed to foreign exchange rate fluctuations and wants to filter out this risk. The degree to which its cash flows are exposed to currency movements depends not only on firm-specific characteristics, such as the proportion of foreign sales or purchasing costs, but as well on factors beyond the firm's control, namely the behavior of its competitors and the competitiveness in the market (Bodnar and Wong, 2003). The exposure to external risks can thus often be seen as risky itself and the term exposure risk refers to this concept.

Göx (2016) provides a first analytical foundation what the presence of exposure risk in a RPE setting implies in terms of peer group choice and the possibility to filter out common noise. The author takes amongst others the example of a focal firm, which compensates its manager based on the own firm performance and the one of a peer index. This peer index contains a set of peer firms, which all share a common risk with the focal firm. Both the focal and all peer firms are assumed to have a random exposure to the common risk. Göx (2016) shows then that the random exposure precludes perfect filtering. The higher the exposure risk is, the less useful becomes the RPE contract.

2.3 Time-varying risk exposures

The intuition of a random or time-varying exposure is very recent in the RPE literature and thus only few address this concern. I enlarge my literature overview with some investigations of other time-varying exposures. This allows me to describe the methods which can be applied in order to estimate the exposure risk.

In the CAPM literature, there are numerous empirical studies on time-varying market betas. Those papers provide amongst others a wide set of methodological approaches to address the problem of exposure risk. Generally spoken, the market betas are estimated at different points in time and if the they show a high fluctuation over time, i.e. a large variance, this is considered to reflect a high exposure risk. The use of rolling regressions is probably the most common approach to estimate time-varying market betas. A second popular method is to model the betas as a (mostly linear) function of observed macroeconomic variables. But there exist numerous other approaches which have been used in the asset pricing literature.

For example, an alternative possibility to model time-varying betas is to use ARCH-class processes, as e.g. Bollerslev et al. (1988). In this case, a conditional covariance matrix is estimated and the elements of that matrix are then used to compute the betas as the ratio of covariance to variance. Especially GARCH-class models and their extensions, such as multivariate GARCH models, are widely used to forecast volatility in CAPM settings. However, the variations in the betas are entirely driven by past innovations and thus do not have an independent random component (Ang and Chen, 2007), which is not what I seek for in this study.

A further approach, which allows stochastic volatility, is to study the dynamics of betas by Kalman filtering, e.g. by using a state space model. One of the main drawbacks in this case is the need to specify the stochastic process of the beta, which in many cases is difficult to motivate (Engle, 2015).

Overall, the CAPM-literature provides large evidence in support of time-varying betas, but in terms of methodology, there has been no consensus established so far. Thus, there still exist many different approaches and the choice of methodology depends on the specific setting of each study.

Another branch in the literature, where time-varying exposures come into play, is the field of exchange rate exposures. However, the method to evaluate the temporal aspect of the currency exposure is usually less sophisticated than in the CAPM-literature. Studies from Jorion (1990), Brunner et al. (2000) or Parsley and Popper (2006) all simply split the available time series of data into different subperiods and investigate whether or not the exposure is the same in all subperiods.

When it comes to currency hedging, there exist analyses which show how exposure risk can limit the ability to filter out the underlying risks. For example, Aabo (2015) describes a setting, where not only the currency rate is uncertain, but as well the quantity which needs to be hedged. In this case, trying to hedge the entire exposure can even be counterproductive, i.e. lead to lower-tail outcomes which are worse than outcomes that involve no hedging at all.

3 Methodology and empirical approach

3.1 The RPE contract

I briefly review a basic RPE contract in an agency setting, where I consider a firm (denoted as the focal firm), which is run by a risk averse agent on the behalf of one or more principals.[18] The agent's payout s is assumed to take the following linear form, as e.g. in Holmström and Milgrom (1987):

$$s_i = w_i + v_i \cdot z_i \tag{36}$$

w is a fixed wage and v_i is the agent's share of the performance measure z_i. z_i on its part contains the own firm performance x_i as well as the performances of its peer firms x_j. $\beta_{i,j}$ is the weight that the focal firm i puts on the peer firm j.

$$z_i(x_i, x_{i,j}) = x_i - \sum_{j=1, j\neq i}^{n} \beta_{i,j} \cdot x_{i,j} \tag{37}$$

[18]Typically, the agent is represented as the manager of the firm. Thus, I will use the terms agent, manager, CEO or executives interchangeably. Similarly, the principal is typically illustrated by the shareholders or the board of directors of the firms, and all three terms are used interchangeably.

When constructing such a performance measure, there are three elements that need to be decided by the principal writing the contract. The first one is how to measure firm performance. I follow previous literature and use equity returns as measure for firm performance. This reflects the predominant evidence that stock return is the most influential factor when it comes to the components of executives' incentive schemes (Core et al., 2003). Consistent with that observation, most empirical RPE studies use equity returns as performance measure, see e.g. Antle and Smith (1986), Albuquerque (2009) or Gong et al. (2011).

The second aspect is the number of peer firms used in the peer group. Every firm that shares some common risks with the focal firm, will have a non-zero correlation with the focal firm's performance. Thus, each of those firms' performances is an informative signal for the focal firm's performance in the sense of Holmström (1979) and should be used as peer. However, it is typically not feasible in practice to consider all firms with a non-zero correlation in the peer group and the number of peer firms needs to be restricted. For example, Gong et al. (2011) investigate disclosed self-selected peer groups of firms and find that the average peer group consists of around 15 peer firms, the 25^{th} and 75^{th} percentile being at 9 and 18 peers, respectively.

In the present study I select peer firms based on their correlation with the focal firm's performance, the details will be provided in section 3.2.1. This is consistent with the informativeness criterion in Holmström (1979) and reflects the traditional theory of stock return comovement. In this view, the correlation between two firm performances reflects comovement in fundamental values, i.e. external shocks affect the expected cash flows of a certain class of firms and their returns will show some correlation.[19] This assumes efficient markets, where stock prices instantly react to such shocks.

A popular approach in selecting a peer group, other than self-select the peers,

[19] There exist other theories which try to explain stock comovement by other factors than fundamentals, e.g. in Barberis et al. (2003) and Barberis et al. (2005). However, those models add possible explanations without neglecting the importance of the fundamentals in stock return comovement.

is to use a given index, e.g. the S&P500. In this case, the number of peers can be very large, but the downside is that the composition and aggregation rule is given and might not be adapted to the specific circumstances of the focal firm.

This leads me to the last aspect, the assignment of the weights $\beta_{i,j}$ to the single peers. In this paper, I refer to the solution in Göx (2016), where the optimal, i.e. variance-minimizing aggregation rule, is derived from a statistical point of view and can be found by a linear regression of the focal firm's performance x_i on the peer firms performances $x_{i,j}$.[20] This regression takes the following form:

$$x_i = \beta_i + \beta_{i,j} \sum_{j=1, j \neq i}^{n} x_{i,j} + \epsilon_i \tag{38}$$

Conducting an OLS regression, one can use the resulting coefficients $\hat{\beta}_{i,j}$ to construct the variance-minimizing performance measure z_i, where the regression coefficients represent the optimal weights of the peer firms within the peer group:[21]

$$z_i(x_i, x_{i,j}) = x_i - \hat{\beta}_{i,j} \sum_{j=1, j \neq i}^{n} x_{i,j} \tag{39}$$

The presence of exposure risk leads now to the following difficulty. The exposure to systematic risks can only be estimated by using historical data and thus reflects the past exposure. However, in practice firms typically choose their peer group ex ante so that the future exposure is relevant for the filtering (Gong et al., 2011). If the exposure varies over time, the estimated coefficient $\hat{\beta}_{i,j}$ might therefore differ from the relevant, future exposure, which essentially prevents perfect filtering. In the worst case, using the wrong betas can even be counterproductive and lead to a variance of z_i which is higher

[20] In cases where the peer group takes the form of a given index, such as the S&P500, the solution can be obtained similarly by regressing the firm's performance on the index performance, i.e. $x_i = \beta_0 + \beta_i \cdot x_{index} + \epsilon_i$.

[21] Again, in case of a given index, the performance measure can be computed similarly and the index performance itself will be weighted by the estimated regression coefficient, i.e. $z_i(x_i, x_{index}) = x_i - \hat{\beta}_i \cdot x_{index}$.

than it would be without filtering.

3.2 Econometric approach

In this section I take the view of a firm aiming to design an efficient RPE contract for its manager. To do so, the firm evaluates the manager's performance on the basis of an aggregate measure of its own performance and the performance of a peer group so that the overall variance of the performance measure is minimized. After the peer group has been established, I investigate how this peer group evolves over time and how well the variance of the performance measure can be reduced compared to a non-RPE contract.

3.2.1 Peer group composition

In a first step, I identify the potential peer firms. While the theoretical prediction is to include all firms which are affected by the same external shocks as the focal firm in the peer group, a focal firm will limit its number of peers for simplicity, as discussed in the previous section.

A common method to create a peer group is to generate an index which contains firms in the same industry as the focal firm. Those industry peer groups have widely been used in RPE studies (e.g. in Antle and Smith (1986), Aggarwal and Samwick (1999a), Janakiraman et al. (1992) or Garvey and Milbourn (2006)). Albuquerque (2009) uses industry-size peer groups, i.e. the peer group not only contains firms within the same industry, but as well firms with similar market capitalization. The authors show that those peer groups provide more evidence in favor of RPE when conducting empirical tests.

However, when it comes to the purpose of filtering out common shocks, firms within the same industry are not necessarily those which best explain stock returns. Hoberg and Phillips (2016) for example, select potential peers on a text-based computational analysis, and find that those can significantly better explain stock return comovements than traditional industry peers. I use the explanatory power of the peer firm as criteria to select the peer group, regardless of any industry classification or other matching criteria. Out of the entire sample, I make a first selection of possible peer firms by regressing the performance of the focal firm i on the performance of each potential peer firm $j \neq i$ individually, i.e. each firm in the entire sample except the focal firm itself.

$$x_i = \beta_i + \beta_{i,j} \cdot x_j + \epsilon_i \tag{40}$$

I keep the firms that meet a certain threshold for the further selection process. More precisely, all firms with a significant regression coefficient at the 5%-level and a R^2 larger than 0.30 will remain in the pool of potential peer firms.[22] However, this approach ignores possible interdependencies between the peer firms. In order to address this issue, I run a stepwise regression with the focal firm as dependent variable and all remaining firms from the regressions in (40) as independent variables.

A stepwise regression permits to choose the most relevant variables among a large amount of independent variables. More precisely, using a backward selection approach, I start by estimating the full model, i.e. including all remaining potential peers that fulfill the criteria described above.

$$x_i = \beta_i + \sum_{j=1}^{n} \beta_{i,j} \cdot x_j + \epsilon_i \tag{41}$$

After the first iteration, the least significant regressor is removed and the model is re-estimated. This procedure continues until all remaining independent variables are significant, the significance level being set at $p < 0.1$. In the end, the final self-selected peer group of firm i consists of all firms that

[22]The threshold of 0.30 is arbitrarily chosen and is a result of a compromise between setting a higher hurdle in order to get only the most relevant peer firms and a lower hurdle, which would allow to keep more firms in the potential peer group, but with the downside that the group becomes unrealistically large.

remain in the model estimated by the stepwise regression in (41). The estimated coefficient $\hat{\beta}_{i,j}$ will be higher if a peer firm shares the same common risks and reacts to them in a very similar way as the focal firm, compared to other peers with less common risks and which react differently to them.

A popular alternative approach for firms is to rely on a given firm index instead of self-selecting the peers. In empirical implicit RPE test, the most widely used peer indices are the S&P500, industry peer groups or industry-size peer groups (Albuquerque, 2009). In this study, I use those indices for comparison with the self-selected peer group. The industry peer group contains all firms with the same 3-digit SIC level and the industry-size peer group is based on firms with the same 2-digit SIC level and the same size quartile.[23] The focal firm itself is always excluded from the peer group.

Within the indices, I assign an equal weight to all firms, i.e. the performances of the peer indices take the form

$$x_{SIC3} = \frac{1}{n}\sum_{j=1}^{n} x_j^{SIC3} \tag{42}$$

and

$$x_{SIC2SIZE} = \frac{1}{n}\sum_{j=1}^{n} x_j^{SIC2SIZE} \tag{43}$$

respectively. The rule of thumb to equal-weight all peers is widely spread in practice according to anecdotal evidence from firms and compensation consultants. It also has been used as aggregation rule for the peer index in some RPE tests, such as Garvey and Milbourn (2006) or Albuquerque (2009).

[23]Matching the firms on the SIC3-industry and size quartiles would lead to very low peer group sizes. Thus I prefer to use a larger set of firms based on the SIC2-code for the industry-size groups.

3.2.2 Peer group aggregation

After composing the self-selected peer group, I aggregate the peer firms into a peer index by assigning the weight $\beta_{i,j}$ to each peer firm. As described in equation (39), the weight of each peer firm's performance is the regression coefficient obtained by estimating the regression in (41). The performance measure thus becomes

$$z_i(x_i, x_{i,j}) = x_i - \hat{\beta}_{i,j} \sum_{j=1}^{n} x^p_{i,j}, \tag{44}$$

where x^p is the set of peer firms that has been chosen by the stepwise regression described in the previous section. This is essentially the same as in equation (37), except that x^p is now a subset of all potential peer firms. The aggregation rule takes into account the individual exposure of the focal firm's performance x_i against each peer firm's performance x_j.

To compare the results to the procedures used in previous literature, I additionally construct an equal-weighted peer index z^{ew}_i as follows: I again take the peer firms estimated by the regression in (41), but instead of using the regression based weighting scheme, I simply assign equal weights to each peer firm. This peer group helps to understand the importance of the aggregation rule in terms of risk filtering. It takes the form

$$z^{ew}_i(x_i, x_{i,j}) = x_i - \frac{1}{n} \sum_{j=1}^{n} x^p_{i,j}. \tag{45}$$

For all exogenously given indices, such as the S&P500, the industry and industry-size peer group, I also estimate the individual exposures of the focal firm against the index by an OLS regression and compute the performance measure as follows:

$$z_i(x_i, x_{index}) = x_i - \hat{\beta}_{i,j} \cdot x_{index} \tag{46}$$

3.2.3 Intertemporal peer group composition and aggregation

To measure the stability of the peer group composition and aggregation over time, I divide the sample period T in several subperiods t and conduct the procedure described in section 3.2.1 and 3.2.2 for each subperiod separately. More precisely, I use a rolling regression approach over a window of five years, where the interval is shifted by 12 months after each regression. This procedure generates a time series of estimates which can then be analyzed further.

A key prerequisite for the use of the rolling regressions approach is the assumption that the focal firm's exposure to each peer firm is constant within each subperiod. If this condition is met, the simple OLS regression produces unbiased estimates. The advantage of this non-parametric approach is that it requires no assumptions about the functional form of the exposure or its determinants (Lewellen and Nagel, 2006).

On the one hand, this approach allows to estimate the exposure risk. Using the time series of estimated exposures from regression (40), I calculate the variance of the focal firm's exposure to each of its peer firms as:

$$R_{i,j} = Var(\hat{\beta}_{i,j,t}) \tag{47}$$

A high variance reflects a high exposure risk $R_{i,j}$. I will include this term as an explanatory variable in the subsequent analyses to investigate how the exposure risk is associated with variations in the peer group composition and how it affects the filtering effectiveness.[24]

On the other hand, the rolling regression approach permits to reassess the optimal peer group composition and aggregation every year. For a single firm, there are up to 22 peer group compositions possible, the first peer

[24]Because I use the entire time series of the estimated coefficients $\hat{\beta}_{i,j,t}$, the exposure risk remains constant for the entire period. The variable $R_{i,j}$ is therefore different for each pair of focal and peer firm, but does not vary with time.

group stems from the regression period 1990-1994, the last one from 2011-2015. However, in most cases there are less than 22 observations per firm due to several reasons.

First, data are not available from 1990 on for several firms. Second, when regressing the performance of the focal firm on the performance of all other firms individually, as in (40), I require a minimum of three potential peer firms to meet the threshold criteria of $R^2 = 0.3$ and $p < 0.1$ as well as a minimum of three firms to be in the final peer group. This reflects the idea that a firm with very low comovement with other stocks and low explanatory power shares only few common risks, so that no reliable peer group can be constructed.

I investigate how the peer group composition varies over time by looking at the proportion of peer firms that remain in the group from one period to the next. If the exposure to common risks remains constant over time, the comovement between the stock returns will be rather stable and the selected peer group will not experience much change over time. Else, because of the variations in the correlations between firms over time, i.e. the exposure risk, the peer group might differ from one period to another.

The method of rolling regression does not only result in a possibly different peer group composition every year, but of course, the regression coefficients and thus the peer group aggregation does as well change after each iteration. Even if the firm is maintained in a peer group for several years, its weighting within the group will typically change in each period. This fact potentially affects the filtering effectiveness, which I describe in section 3.3.

When using a given stock or industry index as a peer group, I also perform a rolling regression over a measurement period of five years and with an interval of one year to estimate the exposure of the focal firm to the peer index at different points in time:

$$x_{i,t} = \beta_{0,i,t} + \beta_{i,t} \cdot x_{index,t} + \varepsilon_{i,t} \tag{48}$$

The estimated index exposure $\hat{\beta}_{i,t}$ allows afterwards to compute the performance measure as in (46).

3.2.4 Determinants of the peer group composition

To further analyze the changes in the composition of the peer group over time, I investigate the factors determining whether a peer firm remains in the peer group one year after its selection. To do so, I use the following logistic regression:

$$\begin{aligned} Prob(KEEP^{1yr}_{i,j,t} = 1) \quad = \quad & \Phi(\alpha_0 + \alpha_1 \cdot SIC2_{i,j} + \alpha_2 \cdot SIC3_{i,j} + \alpha_3 \cdot SIZE_{i,j,t} \\ & + \alpha_4 \cdot SIC2_{i,j} \times SIZE_{i,j,t} + \alpha_5 \cdot SIC3_{i,j} \times SIZE_{i,j,t} \\ & + \alpha_6 \cdot R_{i,j} + \varepsilon_{i,j,t} \qquad (49) \end{aligned}$$

I include all firms that have been selected as peer firms as the basic population (46'027) and assign the value one to each firm that remains in the peer group one year later (13'682), and zero if it drops out (32'345).[25] To examine the robustness of the peer group composition over longer time horizons, I also construct samples, where the dependent variable takes the value one if the firm remains in the peer group two and three years after their selection. This is indicated by the superscript $KEEP^{2yrs}$ and $KEEP^{3yrs}$, respectively.

The independent variables take the value of one if the peer firm is in the same industry (*SIC2* or *SIC3*) or in the same size quartile (*SIZE*) as the focal firm or both (interaction terms of the industry variables and the size variable), zero otherwise. The exposure risk $R_{i,j}$ is defined as variance of the estimated peer firm exposures, as described in equation (47).

The proportion of peers that are maintained versus the peers that are dropped

[25] There are 51'693 peer firms available. However, 5'666 out of them have been estimated over the period 2011-2015 and it cannot be evaluated whether they remain in the peer group or not one year later, since the sample data ends in 2015. The sample size for the regression (49) is thus 46'027.

is around 30% for the variable $KEEP^{1yr}$, but much lower for the second and third year. A balanced sample is important to obtain unbiased and efficient estimates from a logistic regression (Gong et al., 2011). Thus I use the undersampling method to create balanced samples as e.g. in Gong et al. (2011). For example, amongst the 32'345 peer firms which drop out one year after their selection, I randomly select 13'682 for the regression analysis. The random selection and the regression are repeated several times to ensure the robustness of the results.

3.3 Evaluating the filtering effectiveness

The objective of the performance measure $z_i(x_i, x_{i,j})$ is to reduce the variance compared to a simple compensation scheme based on the focal firm's raw performance x_i only. The variance of x_i and, using the peer group selection and aggregation procedure explained above, the variance of $z_i(x_i, x_{i,j})$ can be computed and compared to each other to verify if

$$Var(z(x_i, x^p_{i,j})) < Var(x_i). \tag{50}$$

I consider the filtering as effective whenever the condition in (50) is met. Moreover, I assess the degree of the filtering effectiveness E by the proportion of the variance filtered out from the focal firm's performance, i.e.:

$$E_i = \frac{Var(x_i) - Var(z(x_i, x^p_{i,j}))}{Var(x_i)} \tag{51}$$

I evaluate the filtering effectiveness on an ex post as well as on an out-of-sample basis. To do so, I define a measurement period, during which I run the regressions for the peer group composition and aggregation, and a filtering period, for which I compute the variance of the performance measure.

For example, if the filtering is done ex post, the measurement period lasts from 2010 to 2014 and z is computed for the last year within this period, i.e. for the year 2014 in this example. Since the filtering period is a subset of the measurement period, this scenario converges to a perfect filtering, where the measurement and the filtering periods are identical.

However, in practice firms typically choose peer groups ex ante or agree upon the RPE-based performance targets at the beginning of an incentive program, so that the future performance of the focal firm and its peer group determines the effectiveness of the filtering (Gong et al., 2011). The measurement period thus generally precedes the filtering period.

For example, if a firms selects and aggregates its peer group based on the historical information from 2010 to 2014, it applies the filtering to the year 2015. In this case, the peer group estimated during the measurement period is an imperfect forecast of the relevant peer group in the filtering period and therefore precludes perfect filtering. In cases where the lag between the measurement and filtering period is one year, I refer to this practice as a one year out-of-sample filtering. Likewise, I compute the two and three years out-of-sample filtering.

3.3.1 Determinants of the filtering effectiveness

I obtain the filtering effectiveness of each firm and year, where a self-selected peer group is available. This results in a new panel data set which I further analyze. It is interesting to investigate whether certain firm or peer group characteristics can explain the variation in the filtering effectiveness. The results can provide an insight about the determinants of the filtering effectiveness. I thus investigate the filtering effectiveness by conducting the following pooled regression:

$$\begin{aligned} E_{i,t} \quad = \quad & \gamma_0 + \gamma_1 \cdot PEERS_{i,t} + \gamma_2 \cdot R_i + \gamma_3 \cdot SIC2_{i,t} + \gamma_4 \cdot SIC3_{i,t} \\ & + \gamma_5 \cdot SIZE_{i,t} + \gamma_6 \cdot SIC2SIZE_{i,t} + \gamma_7 \cdot SIC3SIZE_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{52}$$

E_i is the filtering effectiveness as computed in equation (51). I use E_i ex post as well as out-of-sample as dependent variable for the regression analysis. If the dependent variable E_i is evaluated one, two or three years out-of-sample, the independent variables are lagged by one, two and three years, respectively.

I include the exposure risk as a possible determinant for the filtering effectiveness. Since $R_{i,j}$ is measure for each peer firm j separately, an aggregation is necessary to obtain a single exposure risk measure for the entire peer group. As for the aggregation of peer firms into peer groups, I use the estimated coefficients from the stepwise regression (41), $\hat{\beta}^{sw}_{i,j}$, to compute R_i:

$$R_i = \sum_{j=1}^{n} \hat{\beta}^{sw}_{i,j} \cdot R_{i,j} \tag{53}$$

It is one of the main purposes of this study to investigate how exposure risk affects the filtering effectiveness. The theoretical prediction is that a high exposure risk precludes perfect filtering (Göx, 2016). The higher the exposure risk, the lower is the usefulness of RPE and therefore the filtering effectiveness. Thus, I expect a negative coefficient for the variable R_i.

The other independent variables are the number of peers in the peer group (*PEERS*), the share of firms within the peer group belonging to the same industry as the focal firm (*SIC2* and *SIC3*), the share of firms in the same size quartile as the focal firm (*SIZE*) and the share of firms within the same industry and same size quartile (*SIC2SIZE* and *SIC3SIZE*).

I expect the number of peers to be positively correlated with E, since each additional peer that exhibits a non-zero correlation with the performance of the focal firm, contributes to explaining the variance of the focal firm's performance. I also expect a positive regression coefficient for the industry and size variables, since peer groups with a high share of firms within the same industry or size quartile as the focal firm are supposed to share more common risks with the focal firm (Albuquerque, 2009).

4 Data

The sample consists of all S&P500 firms. I include both financial as well as non-financial firms, because I expect no differences between those firms in terms of RPE usage or the ability to use RPE for filtering purposes. I use 26 years of data (1990-2015) and collect monthly stock returns, which allows me to obtain a time series of exposures long enough to assess its time-variation. I exclude firms with less than five years of consecutive data and winsorize the stock return and market value variables at the top and bottom 1%-level to mitigate the effect of outliers. If different classes of shares from the same company are listed, I exclude all except of one class. The performance is measured by equity returns (computed as total shareholder return). Panel A of table 1 presents the summary statistics of the data. The sample contains 472 firms with a total of 127'224 stock return observations and a monthly mean return of around 1.02%. The market value of equity is used to compute size quartiles at the beginning of each year.

[please insert table 1 about here]

Panel B shows the summary statistics of the industry and industry-size peer groups. The industry peer group consists on average of around 10 firms, the largest industry contains 23 firms. The average number of firms in the industry-size peer group is 9 and the largest group contains 20 firms. In both cases, the minimum size required for the analysis is fixed at three firms. The focal firm is always excluded from the peer group, i.e. the peer group is slightly different for every focal firm. This is also the reason for the high number of returns observations (94'183 and 107'078 respectively). I compute the returns as an equal-weighted index of all firms within the industry or industry-size peer group as shown in the equations (42) and (43). The average return of those groups is .010, which is roughly the same as for the individual stock returns. The S&P500 index contains 311 observations, which corresponds to 26 years of monthly returns.

Panel C presents the descriptive statistics for the self-selected peer groups estimated with the procedure described in 3.2.1. These summary statistics are also valid for the equal-weighted self-selected peer groups as described in equation (45), since the composition is the same in both cases.

The average peer group contains about 7.5 firms, which is less than the industry peer group or the industry-size group. The largest peer group comprises 45 firms. However, this is an exception, since the majority of the peer groups contain between three and twenty firms (the 95^{th} percentile being at 20). Overall, I can find 6920 self-selected peer groups accommodating a total number of 51'693 firms. Around 16.4% of those peers are in the same SIC3 industry as the focal firm (8'490 out of 51'693) and around 7.8% of the self-selected peers also appear in the industry-size peer group of the focal firm (4'022 out of 51'693).

5 Main results

5.1 Peer group composition over time

In this section I analyze on a firm-level basis how the peer group composition varies over time. For this part of the analysis, I ignore the weighting of the peers within the group and address it only in the next section. Table 2 presents the results and can be interpreted as follows. Given a peer group at time t, only 29.7% of the firms remain in the peer group at $t+1$, i.e. in the next year. Three years later, the original peer group in t has largely been replaced, the proportion of firms that are selected in $t+3$ represent just 16.6% of the original group. In absolute numbers, if I take the average peer group size of 7.47 peer firms, only 2.22 of these firms are the same peers as in the previous year, whereas the remaining part (5.25) of the peer group has been newly added to the peer group.

[please insert table 2 about here]

As shown in table 1, only 16.4% of the peer firms have the same SIC3-digit code as the focal firm (8'490 out of 51'693). In an average peer group there are thus only 1.23 peer firms from the same industry. However, the industry peers seem to be slightly more stable. After one year, 48.1% of these peers remain in the peer group and even after three years, 36.1% are kept as peer firms. Similarly, the peer firms within the same industry (SIC2) and size quartile as the focal firm are also less likely to be replaced. 47.5% of the selected peer firms remain in the peer group of that focal firm after one year, which is a slightly lower percentage than for the industry-only peers, but higher than for the general peer firms.

5.1.1 Determinants of the peer group composition

The next step of the analysis considers all firms that have been chosen as peer firms at any point of time. Within this new sample, I evaluate for each peer firm whether it remains in the peer group one, two or three years later. I run the logistic regression model (49) and obtain the results presented in table 3. First, the pseudo R^2 of just 4.57% to 9.37% indicates a low model fit. This suggests that there might be other peer group or firm characteristics which better determine the peer group stability. Nevertheless, there are some interesting findings regarding the peer group composition.

Overall, the results confirm the findings from the previous section and assure their statistical significance. Furthermore, the results are very similar in all columns. No matter if one looks at the composition one, two or three year ahead, the significant determinants are almost always the same.

[please insert table 3 about here]

Peer firms which belong to the same industry are more likely to remain in the peer group in the following years. This holds for both industry levels

SIC2 and SIC3, respectively. Similarly, the probability to remain in the peer group is significantly higher for peers with the same size quartile as the focal firm.

If a peer firm belongs to the same industry and to the same size quartile as the focal firm, the coefficients add up, meaning that the probability to remain in the peer group is even higher than for peers matching on industry or size only. However, the estimate of the interaction variables $\mathit{SIC2} \times \mathit{SIZE}$ and $\mathit{SIC3} \times \mathit{SIZE}$ are not significant. The combination per se of being a peer firm in the same industry and of the same size as the focal firm does therefore not additionally increase the probability to remain in the peer group.

The coefficient $R_{i,j}$ is significant at the 1%-level in the column '3 years'. This means, that a stable exposure against the focal firm is associated with a higher probability of being chosen as peer three years later. However, the result is ambiguous, because the coefficients for the columns '1 year' and '2 years' are not significant.

5.2 Peer group aggregation and filtering

I next consider the aggregation of the peer group in addition to its composition. To do so, I compute the performance measure z and analyze the filtering effectiveness E. First, I present the results where I use the S&P500 index, the industry- and the industry-size peer group to filter out the systematic risks (Table 4, Panel A-C). The four columns show the time differences between the estimation periods and the filtering period. $t = 0$ is the ex post view and $t = 1, 2, 3$ are the out-of sample views. For example, in $t = 3$ I take the peer group estimated using the data from 1990-1994 to filter out common risks in 1997.

The first row of each panel shows the number of estimated variances. The variances are calculated for each firm and year separately and one firm-year variance counts as one observation. However, I count the observation $Var(x_i)$

only if $Var(z_i)$ exists as well for the same firm and year. This is the reason why the number of observations decreases from $t = 0$ to $t = 3$. In Panel B for example, the first column contains 7'064 firm-year variances, because data from 1994 until 2015 can be taken into account. For the column $t = 3$, the first available observation for $Var(z_i)$ occurs in the year 1997 (taking the first estimation period from 1990 to 1994 and adding three years) and therefore, only 5'962 firm-year variances can be computed.

The second row presents the mean of all firm-year variances of the focal firm's monthly stock returns x_i. It can be seen that $Var(x_i)$ is roughly the same between and also within all panels. This is not surprising, since the underlying data is basically the same, the only difference being that not always all observations are used. The third row does the same calculation except that I now compute the variance of the aggregate performance measure z, i.e. the filtered stock returns. One can see that the filtering is on average effective in all cases since $Var(z_i)$ is strictly smaller than $Var(x_i)$. In Panel B, for example, the average yearly variance is .00936 for the unfiltered returns and .00613 for the filtered returns. The absolute reduction achieved by RPE is thus .00323, as shown in the fourth row. The filtering effectiveness, i.e. the relative reduction in variance, is 34.52% as shown in the last row.

[please insert table 4 about here]

A view at the differences between and within the panels provides some interesting insights. For example, the first column (ex post filtering) shows that using the S&P500 index to filter out the systematic risks leads to the lowest filtering effectiveness. The average variance $Var(x_i)$ can be reduced by 25.93% compared to 32.24% for the industry-size peer group and 34.52% for the industry peer group. This finding suggests that industry and industry-size peer groups can better explain the variance of the focal firm than the S&P500 index. However, between the industry and the industry-size peer group there seems to be no major difference. The industry-only index, containing all firms with the same SIC3-digit code as the focal firm, even per-forms slightly better the industry-size index, containing firms with the same SIC2-digit code and the same size quartile as the focal firm. Ex post, the highest filtering effectiveness is achieved by the beta-weighted self-selected peer group (72.21%).

Within each panel, one can observe that the filtering effectiveness weakens as the time difference between the estimation and the filtering period increases. The biggest decline occurs between the ex post view $t = 0$ and the one year out-of-sample view $t = 1$. For example, in the equal-weighted self-selected peer group the efficiency decreases from 45.91% to 22.89%. From $t = 1$ to $t = 3$ the variance reduction is surprisingly constant and decreases only slowly. In panel C the effectiveness remains virtually the same and even slightly increases to 29.91% in $t = 3$.

The strongest decrease in the effectiveness appears in the self-selected peer groups, especially when the aggregation rule for the performance measure z is based on the estimated betas as described in equation (46). Panel E presents the results. Both self-selected peer groups only outperform the other indices ex post, otherwise they perform worse. For example, the decrease from $t = 0$ to $t = 1$ is by far the largest for the beta-weighted self-selected peer group as the effectiveness decreases from 72.21% to 8.75%.

The comparison between panel D and E is particularly interesting, because the only difference between the two peer groups is the aggregation rule, while the composition is exactly the same in both cases. Every difference in the results is therefore due to the aggregation rule. It shows how the exposure risk leads to less efficient filtering. Due to the time-variation in the exposure, the out-of-sample filtering is worse for the beta-weighted peer group than for the equal-weighted one. For example, the filtering period $t = 3$ shows a value of 1.43% in panel E. This means that the variance of the filtered returns is barely lower than with raw returns. In such a case, using RPE to filter out systematic risks is essentially useless.

Overall, it seems that the self-selected peer groups provide good results ex post, but are much less constant than the given indices. For example, the industry peer group exhibits the largest filtering effectiveness in the out-of-sample specifications. A firm might thus prefer to rely on exogenously given indices to filter out systematic risks rather than constructing a firm-specific peer group.

5.2.1 Determinants of the filtering effectiveness

So far, the results indicate that the self-selected peer groups perform poorly in filtering common risks in out-of-sample periods. This observation is particularly pronounced for the beta-weighted aggregation rule. However, these results are based on sample averages, whereas the filtering effectiveness varies considerably among individual firms. It is thus interesting to examine whether certain firm or peer group characteristics can explain the variation of the filtering effectiveness.

Table 5 shows the result of this analysis. The first column presents the ex post view, i.e. when the ex post filtering effectiveness is taken as the dependent variable. The positive and significant estimate for the variable *PEERS* shows that an increase in the peer group size is associated with a higher filtering effectiveness. Similarly, the higher the fraction of firms belonging to the same SIC-3 industry, the higher is E. The variables *SIZE*, *SIC2SIZE*, *SIC3SIZE* and the exposure risk R are not significantly related to the ex post filtering effectiveness.

[please insert table 5 about here]

The results change considerably for the out-of-sample estimates in columns 2-4. For example, the second column reports the estimates if the filtering effectiveness is computed one year out-of-sample. An interesting finding is that the peer group size is now negatively associated to E, whereas the coefficient is positive for the within sample estimate. An increase in the peer group size is therefore related with a lower out-of-sample filtering effectiveness. This finding questions the view that a larger peer group is more efficient in filtering common risk from the focal firm's performance. A possible interpretation for this result is that each additional peer firms also potentially adds exposure risk. However, since I also include the exposure risk in the regression, this effect should be captured by the variable R.

The variable *SIC3* is significant for all specifications. Peer groups with a higher proportion of firms belonging to the same SIC3-industry as the focal firm, exhibit on average a higher filtering effectiveness. This supports the fact that firms tend to choose peers within their industry (see e.g. Albuquerque (2013) or Gong et al. (2011)). On the other hand, I do not find that choosing peers in the same SIC-2 industry or peers with a similar market capitalization helps to reduce the variance of the focal firm's stock return. Only in the last column, the estimate for the variable *SIZE* is positive and significant.

The variable R is significantly negative for all out-of-sample specifications. This finding of great interest in this study, because it supports the theoretical prediction that a high exposure risk can negatively affect the usefulness of RPE. Peer groups with a high exposure risk, i.e. where the peer firms' exposure to the focal firm varies over time, have a lower filtering effectiveness. Vice versa, a more stable peer group is associated with a higher filtering effectiveness out of sample.

The comparison of the estimates for the different time horizons can provide some additional information. The exposure risk coefficients are increasing with the forecasting horizon. For example, their value is -13.7 for the one year horizon and -20.6 for the three year horizon. Thus, the longer a firm sticks to the same peer group composition and aggregation, the more harmful is the exposure risk for the filtering purpose of RPE.

6 Robustness checks

6.1 Peer group composition

In the main part of the study I already presented the results for different peer group compositions. Namely, I compared the self-selected peer group with commonly used indices, such as an equal-weighted industry index (based on the SIC2- and SIC3-codes) and the S&P500. There are of course numerous ways to establish a self-selected peer group. In any case, the focal firm's performance will potentially show a time-varying correlation to the performance of the selected peer firm, because the underlying exposure to the common risk varies over time. Thus, I do not expect that the main findings regarding the filtering effectiveness will alter for different peer firm selection criteria.

In my study, I use two steps to establish the peer group. First, I select a group of potential peers based on simple OLS regressions. Second, I choose the peer firms within this group based on a stepwise regression. As a variation to the main part of the study, I now modify the selection criteria of the second step and show the impact on the peer group composition and filtering effectiveness. To do so, I increase the significance level for the selection of peer firms to $p < .05$ (instead of $p < .1$). The higher hurdle decreases the number of selected peers, but the average peer firm is now expected to share even more common risks with the focal firm.

[please insert table 6 about here]

Table 6 shows the impact of restricting the significance level for the peer group selection. This change results in an average peer group size of 5.19 firms instead of 7.47. However, at the same time the smaller peer group appears to be more stable over time. For example, 34.6% of the initial peers are still part of the peer group three years later as compared to 16.6% with the lower selection hurdle of $p < .1$. Peer firms with the same industry or industry-size characteristics as the focal firm are again less likely to be removed from the peer group. This effect is now even stronger than in the main part of the study.

6.2 Determinants of the peer group composition

I run again the logistic regression from model (49) and now include different control variables to examine whether those variables better explain the probability of a peer firm to remain in the peer group or whether the inclusion of control variables change the main results.

First, I add the size quartile of the focal and the peer firm. Controlling for size reflects the idea that larger firms might be more stable in terms of their exposure to systematic risks. It is more difficult for them to quickly react to new trends or to reorganize their strategy and/or their products. A large peer firm might therefore have a higher probability to remain in the peer group, especially if the focal firm is large as well (for this reason I add the interaction term between those variable). Second, I add the peer group size as control variable. If a firm has a large peer group, the probability for a peer firm to remain in the group might be higher simply because there are more free slots to be assigned.

[please insert table 7 about here]

The results shown in table 7 confirm the main findings in section 5.1.1. The variables *SIC2* and *SIC3* are still significant at the 1%-level in all three columns. The exposure risk R is again only significant in the column '3 years' and the interaction terms *SIC2* $\times$ *SIZE* and *SIC3* $\times$ *SIZE* cannot be distinguished from zero except for one case. The magnitude of the coefficients is as well very similar to the main results, the R-squared is slightly higher, mainly due to the inclusion of the variable *PEERS*.

One different result is that the coefficient *SIZE* is not significant anymore. In contrast, the interaction term $SIZE^F \times SIZE^P$ is significantly positive in all cases. This result provides some support for the hypothesis that larger peer firms are more stable if the focal firm is large as well. The peer group size *PEERS* has a significant negative coefficient, which is against the expectation. However, this does not affect the other estimates and does not change the overall interpretation from the main results.

6.3 Analysis of the filtering effectiveness

To examine the robustness of the results in section 5.2.1, where the filtering effectiveness is analyzed, I use regression model (52) and add different control variables. First, I include the size quartile of the focal firm. The reason for including this variable is that it might be easier for large firms to detect other firms with some similarities. Small firms, which often occupy a market niche, might face more difficulties to find firms with a similar risk exposure.

Second, I add the variable R^2. It takes the value of the coefficient of determination obtained from the stepwise regression in (41) during the estimation period, which I used to identify the initial peer group. In the ex post view, there is certainly a positive coefficient (since the peer group has explicitly been chosen in a way to obtain a high R^2), but I also expect this positive relation to hold for the out-of-sample filtering effectiveness.

[please insert table 8 about here]

Overall, the results shown in table 8 are very similar to the main results in section 5.2.1. The peer group size is positively associated with the filtering effectiveness in the ex post view and negatively in the out-of-sample view. The coefficient on the exposure risk R remains significant at the 1%-level for all out-of-sample specifications.

The variable R^2 is not only positive and significant in the column 'ex post', but as well in all other columns. A high R-squared in the estimation period is thus associated with a higher filtering effectiveness in out-of-sample periods. This observation indicates that the method of choosing peer firms based on the approach in this study, i.e. by using the stepwise regression model (41), has at least some abilities to filter out systematic risks in later periods. The second control variable included, $SIZE^F$, has no significant effect on the dependent variable E.

7 Conclusion

This study investigates how the presence of exposure risk, i.e. the time-variation in the exposure to systematic risks, affects the filtering purpose in RPE settings. In a first step, I estimate the exposure of a firm's performance to the performance of potential peer firms in order to construct a firm-specific peer group. Using a rolling regression approach, I then assess the exposure risk and examine how the peer group composition evolves over time. Finally, I compute and investigate the filtering effectiveness, i.e. the relative variance reduction achieved by using RPE.

The exposure risk affects both the composition and the aggregation of a peer group. Taking a peer group at a certain point in time, I find that only 16.6% of the peer firms are left in the group three years later. Peer firms from the same industry or same size as the focal firm are more likely to remain in the peer group. In contrast, the exposure risk has no clear relation with the probability to remain in the peer group one or two years later.

The main point of the study is the examination of the filtering effectiveness. The results provide evidence that the presence of exposure risk affects the filtering effectiveness in RPE settings. While the self-selected peer group can explain the largest proportion of the focal firm's equity return variance within the sample period, this result does not hold for the out-of-sample periods. However, the out-of-sample view is more important, because the peer group is typically chosen ex ante and the RPE-based performance targets are agreed upon at the beginning of the period for which the performance should be evaluated. The observed difference from the ex post and out-of-sample filtering results is due to the exposure risk. With constant exposure, there would be no such difference.

Interestingly, simple peer indices such as the S&P500 or industry peer groups show better out-of-sample filtering abilities than the self-selected peer group. One possible interpretation is that the exposure to such indices is more stable over time and can thus better filter out systematic risks in out-of-sample periods.

I further analyze the filtering effectiveness of the self-selected peer group and find that the peer group size and the exposure risk are significantly associated to the out-of-sample filtering effectiveness. Peer groups with a high exposure risk show on average a lower filtering effectiveness. This effect becomes stronger with an increasing time horizon, i.e. a given increase in the exposure risk is more harmful for the 3-years out-of-sample filtering than for the 1-year out-of-sample filtering.

The results in this study provide evidence for an additional explanation of the RPE puzzle. Firms prone to a high exposure risk might prefer standardized instead of self-constructed peer groups or even refrain from RPE due to its low ability to remove the exposure of the firm's performance to common risk. Future research can investigate how the exposure risk can be taken into account to further optimize the peer group composition and aggregation. This could provide insights on the possibility to use RPE effectively, even in presence of exposure risk.

Tables and figures

Table 1: Summary statistics

Panel A: Basic data	N	Mean	sd	Min	Max
Firm characteristics:					
stock return	127’224	.010	.099	-.851	.914
market value ($ millions)	127’224	19’416	39’916	2.5	752’015
Panel B: Benchmark peer groups:					
Size:					
Industry (SIC3)	53	10.26	6.09	3	23
Industry-size (SIC2 & size)	91	9.40	4.32	3	20
Returns:					
Industry (SIC3)	94’183	.010	.071	-.514	.416
Industry-size (SIC2 & size)	107’078	.010	.068	-.416	.442
S&P500	311	.008	.042	-.113	.104
Panel C: Self-selected peer groups:					
Peer group characteristics:					
Size	6920	7.47	5.76	3	45
Peer firm characteristics:					
total number of peer firms	51’693				
- thereof same SIC3	8’490	1.23	1.80	0	19
- thereof same SIC2 & size	4’022	.58	.94	0	9

The table shows the number of observations (N), the mean value (Mean), the standard deviation (sd), the minimum value (Min) and the maximum value (Max) for each variable.
The sample period lasts from 1990 to 2015 and contains monthly data. The sample comprises 471 firms from the S&P500 with overall 127’224 monthly return observations.
Panel A describes the firm characteristics. The stock returns are computed as $ln(\frac{R_{i,t}}{R_{i,t-1}})$, R being the total return index from Datastream.
Panel B describes the size and the returns of the benchmark peer groups. Both the industry and the industry-size peer group are computed as equal-weighted index, where the focal firm itself is excluded.
Panel C describes the regression based self-selected peer group. The first step is to regress the focal firm on all sample firms individually: $x_i = \beta_i + \beta_{i,j} \cdot x_j + \epsilon_i$. I maintain all firms with a significant coefficient at the 5%-level. Then I run a stepwise regression with the focal firm as dependent variable and the firms maintained from the first step as independent variables: $x_i = \beta_i + \sum_{j=1}^{n} \beta_{i,j} \cdot x_j + \epsilon_i$. I provide details to this procedure in section 3.2.1.

Table 2: Peer group composition over time

		$t = 1$	$t = 2$	$t = 3$
avg # of peer firms	7.47			
- thereof maintained after t years		2.22	1.57	1.24
		29.7%	21.0%	16.6%
avg # of peer firms (same SIC3)	1.23			
- thereof maintained after t years		.59	.48	.44
		48.1%	39.4%	36.1%
avg # of peer firms (same SIC2 & size)	.58			
- thereof maintained after t years		.26	.23	.20
		47.5%	39.5%	35.3%

The first column shows the average number of firms per peer group based on the beta-weighted self-selected peer group. The other columns show the proportion of firms which are maintained in the peer group one, two and three years later.

Table 3: Analysis of the peer group composition

	1 year	2 years	3 years
SIC2	.655**	.785**	.973**
	(.056)	(.067)	(.077)
SIC3	.409**	.520**	.628**
	(.061)	(.077)	(.088)
SIZE	.127**	.111**	.187**
	(.032)	(.043)	(.051)
SIC2 $\times$ *SIZE*	-.116	-.160	-.338*
	(.099)	(.126)	(.148)
SIC3 $\times$ *SIZE*	.169	.278	.285
	(.113)	(.143)	(.165)
R	-.334	-.431	-2.889**
	(.377)	(.491)	(.609)
Intercept	.255*	-.130	-.274
	(.104)	(.135)	(.165)
observations	27'364	17'216	12'182
Pseudo R^2	4.57%	6.71%	9.37%
Year FE	yes	yes	yes

This table shows the results from regression model (49): $Prob(KEEP_{i,j,t} = 1) = \Phi(\alpha_0 + \alpha_1 \cdot SIC2_{i,j} + \alpha_2 \cdot SIC3_{i,j} + \alpha_3 \cdot SIZE_{i,j,t} + \alpha_4 \cdot SIC2_{i,j} \times SIZE_{i,j,t} + \alpha_5 \cdot SIC3_{i,j} \times SIZE_{i,j,t} + \alpha_6 \cdot R_{i,j} + \varepsilon_{i,j,t}$.
The sample contains all firms which have been chosen as peer firms in the self-selected peer group. The dependent variable takes the value one if the peer firm is still part of the peer group one year later (respectively two and three years later for the columns '2 years' and '3 years') and zero if the peer firm has dropped out from the peer group one year later (respectively two and three years later for the columns '2 years' and '3 years').
The independent variables are defined as follows: *PEERS*=number of peer firms in the peer group. *SIC2*,*SIC3*=1 if the peer firm is in the same industry as the focal firm, zero otherwise. *SIZE*==1 if the peer firm is in the same size quartile as the focal firm, zero otherwise. $R_{i,j}$ =Var($\hat{\beta}_{i,j,t}$), where $\hat{\beta}_{i,j,t}$ are the estimates from regression (40) obtained from rolling regressions.
Robust standard errors are reported in parentheses. * and ** denote statistical significance at the 5% and 1% level, respectively (two-tailed test).

Table 4: Filtering effectiveness over time

	$t=0$	$t=1$	$t=2$	$t=3$
Panel A: S&P500				
observations	9'361	8'889	8'414	7'945
mean $Var(x_i)$	.00869	.00912	.00863	.00856
mean $Var(z_i)$, t years after estimation	.00643	.00703	.00665	.00670
$Var(x_i) - Var(z_i)$	.00225	.00209	.00198	.00187
filtering effectiveness E	25.93%	22.93%	22.97%	21.80%
Panel B: Industry peer group				
observations	7'064	6'697	6'630	5'962
mean $Var(x_i)$	.00936	.00926	.00917	.00901
mean $Var(z_i)$, t years after estimation	.00613	.00623	.00618	.00606
$Var(x_i) - Var(z_i)$	.00323	.00303	.00299	.00296
filtering effectiveness E	34.52%	32.70%	32.57%	32.80%
Panel C: Industry-size peer group				
observations	7'666	7'525	7'112	6'701
mean $Var(x_i)$	.00948	.00925	.00920	.00901
mean $Var(z_i)$, t years after estimation	.00642	.00649	.00645	.00636
$Var(x_i) - Var(z_i)$	.00306	.00276	.00276	.00271
filtering effectiveness E	32.24%	29.84%	29.95%	29.91%
Panel D: regression based peer group (equal-weighted)				
observations	6'920	6'499	6'075	5'669
mean $Var(x_i)$	.00866	.00834	.00813	.00803
mean $Var(z_i)$, t years after estimation	.00468	.00643	.00646	.00639
$Var(x_i) - Var(z_i)$	.00398	.00191	.00167	.00164
filtering effectiveness E	45.91%	22.89%	20.56%	20.39%
Panel E: regression based peer group (beta-weighted)				
observations	6'920	6'499	6'075	5'669
mean $Var(x_i)$	.00866	.00834	.00813	.00803
mean $Var(z_i)$, t years after estimation	.00241	.00761	.00757	.00792
$Var(x_i) - Var(z_i)$	.00625	.00073	.00056	.00011
filtering effectiveness E	72.21%	8.75%	6.90%	1.43%

This table shows the variances and filtering effectiveness for different peer groups (Panel A-D) and filtering periods ($t = 0$ to $t = 3$).

Panel A uses the S&P500 as peer group. $Var(x_i)$ is the variance of the monthly stock returns for a single firm and a single year. mean $Var(x_i)$ is the average $Var(x_i)$ of all firms and years. $Var(z_i)$ is computed as $Var(x_i - \hat{\beta}_{i,j} x_{index})$. The filtering effectiveness is computed as $E_i = \frac{Var(x_i) - Var(z_i)}{Var(x_i)}$.

Panel B uses an equal-weighted return index of all firms within the same SIC-3 industry as the focal firm as peer group.

Panel C uses an equal-weighted return index of all firms within the same SIC-2 industry and the same size quartile as the focal firm as peer group.

Panel D uses the regression based self-selected peer group, giving an equal weight to each peer firm. I provide details on the determination of this peer group in section 3.2.1.

Panel E uses the regression based self-selected peer group. I provide details on the determination of this peer group in section 3.2.1. $Var(z_i)$ is computed as $Var(x_i - \hat{\beta}_{i,j} \sum_{j=1}^{n} x_{i,j}^{p})$, where $x_{i,j}^{p}$ are the firms of the regression based self-selected peer group and $\hat{\beta}_{i,j}$ is their weight within the group.

Table 5: Analysis of the filtering effectiveness

	ex post	out-of-sample		
		1 year	2 years	3 years
PEERS	.0148**	-.1065**	-.1264**	-.1944**
	(.0008)	(.0062)	(.0081)	(.0144)
SIC2	.0064	.0026	.0006	.0734**
	(.0036)	(.0167)	(.0196)	(.0283)
SIC3	.0089*	.1092**	.1232**	.1130**
	(.0043)	(.0189)	(.0230)	(.0352)
SIZE	.0013	-.0059	-.0176	.0608*
	(.0022)	(.0124)	(.0171)	(.0273)
SIC2SIZE	.0543	-.1315	-.1612	-.6578*
	(.0519)	(.1867)	(.1711)	(.3056)
SIC3SIZE	.0341	-.0086	-.3982*	.0021
	(.0569)	(.1892)	(.1791)	(.3153)
R	-.7279	-13.6893**	-19.9085**	-20.5551**
	(.4633)	(2.0150)	(2.7623)	(4.1408)
Intercept	.3852**	.4573**	.7485**	1.0469**
	(.0186)	(.0533)	(.0607)	(.0936)
observations	6920	6499	6075	5669
R^2	29.36%	31.97%	32.45%	26.16%
Year FE	yes	yes	yes	yes

This table shows the results from regression model (52): $E_{i,t} = \gamma_0 + \gamma_1 \cdot PEERS_{i,t} + \gamma_2 \cdot R_i + \gamma_3 SIC2_{i,t} + \gamma_4 \cdot SIC3_{i,t} + \gamma_5 \cdot SIZE_{i,t} + \gamma_6 \cdot SIC2SIZE_{i,t} + \gamma_7 \cdot SIC2SIZE_{i,t} + \varepsilon_{i,t}$.
The dependent variable $E_{i,t}$ differs for each column. 'Ex post' uses the ex post filtering effectiveness, 'out-of-sample' uses the filtering effectiveness one, two and three years out-of-sample. The dependent variable is winsorized at the 1%-level. The independent variables in the columns 'out-of-sample' are lagged by one, two and three years, respectively.
The independent variables are defined as follows: *PEERS*=number of peer firms in the peer group. *SIC2*,*SIC3*=(number of peer firms within the same industry as the focal firm)/(total number of peer firms in the peer group). *SIZE*=(number of peer firms within the same size quartile as the focal firm)/(total number of peer firms in the peer group). *SIC2SIZE*,*SIC3SIZE*=(number of peer firms within the same industry and the same size quartile as the focal firm)/(total number of peer firms in the peer group). $R_i = \hat{\beta}^{sw}_{i,j,t} \cdot \mathrm{Var}(\hat{\beta}_{i,j,t})$, where $\hat{\beta}^{sw}_{i,j,t}$ is the estimate from the stepwise regression (41) and $\hat{\beta}_{i,j,t}$ are the estimates from regression (40), both obtained from rolling regressions.
Robust standard errors are reported in parentheses. * and ** denote statistical significance at the 5% and 1% level, respectively (two-tailed test).

Table 6: Peer group composition over time

		$t = 1$	$t = 2$	$t = 3$
avg # of peer firms	5.19			
- thereof maintained after t years		2.55	2.07	1.80
		49.2%	39.8%	34.6%
avg # of peer firms (same SIC3)	1.29			
- thereof maintained after t years		.94	.84	.79
		72.6%	65.2%	61.4%
avg # of peer firms (same SIC2 & size)	.62			
- thereof maintained after t years		.39	.34	.32
		62.2%	55.4%	51.9%

The first column shows the average number of firms per peer group based on the beta-weighted self-selected peer group. The other columns show the proportion of firms which are maintained in the peer group one, two and three years later.
Different from table 2, I set the significance level in the stepwise regression at $p < .05$ instead of $p < .10$.

Table 7: Analysis of the peer group composition

	1 year	2 years	3 years
SIC2	.605**	.749**	.947**
	(.053)	(.068)	(.078)
SIC3	.419**	.521**	.626**
	(.062)	(.078)	(.089)
SIZE	.060	-.024	.130*
	(.039)	(.051)	(.061)
SIC2 × *SIZE*	-.104	-.171	-.344*
	(.100)	(.126)	(.149)
SIC3 × *SIZE*	.147	.220	.307
	(.114)	(.142)	(.166)
R	-.098	.003	-2.661**
	(.384)	(.501)	(.610)
$SIZE^F$	-.490	-.115*	-.144*
	(.036)	(.047)	(.057)
$SIZE^P$	-.031	-.075	-.058
	(.035)	(.046)	(.056)
$SIZE^F \times SIZE^P$	.027*	.058**	.059**
	(.013)	(.017)	(.020)
PEERS	-.043**	-.031**	-.020**
	(.002)	(.002)	(.002)
Intercept	.507**	.229	-.098
	(.143)	(.153)	(.226)
observations	27'364	17'216	12'182
Pseudo R^2	6.52%	7.62%	10.00%
Year FE	yes	yes	yes

This table shows the results from the following regression model: $Prob(KEEP_{i,j,t} = 1) = \Phi(\alpha_0 + \alpha_1 \cdot SIC2_{i,j} + \alpha_2 \cdot SIC3_{i,j} + \alpha_3 \cdot SIZE_{i,j,t} + \alpha_4 \cdot SIC2_{i,j} \times SIZE_{i,j,t} + \alpha_5 \cdot SIC3_{i,j} \times SIZE_{i,j,t} + \alpha_6 \cdot R_{i,j} + \alpha_7 \cdot SIZE^F + \alpha_8 \cdot SIZE^P + \alpha_9 \cdot SIZE^F \times SIZE^P + \alpha_{10} \cdot PEERS + \varepsilon_{i,j,t}$.
The sample contains all firms which have been chosen as peer firms in the self-selected peer group. The dependent variable takes the value of one if the peer firm is still part of the peer group one year later, zero otherwise.
The independent variables are defined as follows: *PEERS*=number of peer firms in the peer group. *SIC2*,*SIC3*=1 if the peer firm is in the same industry as the focal firm, zero otherwise. *SIZE*==1 if the peer firm is in the same size quartile as the focal firm, zero otherwise. $R_{i,j}$ =Var($\hat{\beta}_{i,j,t}$), where $\hat{\beta}_{i,j,t}$ are the estimates from regression (40) obtained from rolling regressions. $SIZE^F$=size quartile of the focal firm. $SIZE^P$=size quartile of the peer firm. *PEERS*=number of firms in the peer group. Robust standard errors are reported in parentheses. * and ** denote statistical significance at the 5% and 1% level, respectively (two-tailed test).

Table 8: Analysis of the filtering effectiveness

	ex post	out-of-sample		
		1 year	2 years	3 years
PEERS	.0017**	-.1308**	-.1493**	-.2237**
	(.0007)	(.0064)	(.0085)	(.0153)
SIC2	.0007	-.0091	-.0123	.0570*
	(.0033)	(.0162)	(.0192)	(.0278)
SIC3	.0004	.0942**	.1106**	.0975**
	(.0037)	(.0186)	(.0226)	(.0351)
SIZE	-.0024	-.0146	-.0270	.0513
	(.0020)	(.0119)	(.0167)	(.0268)
SIC2SIZE	.0258	-.1772	.1298	-.6936*
	(.0475)	(.1820)	(.1675)	(.3050)
SIC3SIZE	.0479	.1634	-.3856*	.0237
	(.0518)	(.1855)	(.1767)	(.3171)
R	-.5513	-13.1129**	-19.2282**	-19.9713**
	(.4156)	(1.9927)	(2.7610)	(4.1752)
$SIZE^F$	.0012	.0080	.0136	-.0010
	(.0027)	(.0094)	(.0123)	(.0192)
R^2	1.0007**	1.899**	1.8171**	2.2380**
	(.0279)	(.1049)	(01339)	(.2241)
Intercept	-.1630**	-.6007**	-.2802**	-.1673
	(.0243)	(.0710)	(.0821)	(.1314)
observations	6920	6499	6075	5669
R^2	40.78%	35.49%	34.64%	27.65%
Year FE	yes	yes	yes	yes

This table shows the results from regression model (52): $E_{i,t} = \gamma_0 + \gamma_1 \cdot PEERS_{i,t} + \gamma_2 \cdot R_i + \gamma_3 \cdot SIC2_{i,t} + \gamma_4 \cdot SIC3_{i,t} + \gamma_5 \cdot SIZE_{i,t} + \gamma_6 \cdot SIC2SIZE_{i,t} + \gamma_7 \cdot SIC2SIZE_{i,t} + \gamma_8 \cdot SIZE^F + \gamma_9 \cdot R^2 + \varepsilon_{i,t}$. The dependent variable $E_{i,t}$ differs for each column. 'Ex post' uses the ex post filtering effectiveness, 'out-of-sample' uses the filtering effectiveness one, two and three years out-of-sample. The independent variables in the columns 'out-of-sample' are lagged by one, two and three years, respectively. The independent variables are defined as follows: *PEERS*=number of peer firms in the peer group. *SIC2*,*SIC3*=(number of peer firms within the same industry as the focal firm)/(total number of peer firms in the peer group). *SIZE*=(number of peer firms within the same size quartile as the focal firm)/(total number of peer firms in the peer group). *SIC2SIZE*,*SIC3SIZE*=(number of peer firms within the same industry and the same size quartile as the focal firm)/(total number of peer firms in the peer group). $R_i=\hat{\beta}^{sw}_{i,j,t}\cdot$ Var$(\hat{\beta}_{i,j,t})$, where $\hat{\beta}^{sw}_{i,j,t}$ is the estimate from the stepwise regression (41) and $\hat{\beta}_{i,j,t}$ are the estimates from regression (40), both obtained from rolling regressions. $SIZE^F$=size quartile of the focal firm. R^2=R-squared value from the stepwise regression (41) during the estimation period.
Robust standard errors are reported in parentheses. * and ** denote statistical significance at the 5% and 1% level, respectively (two-tailed test).

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Time-variation in the exchange rate exposure of Swiss firms

Abstract

This study measures the exchange rate exposure of Swiss firms for its most relevant currencies and assesses its time-variation. I find that the firm-level exposure varies considerably over time. Differences in operational possibilities to mitigate the exposure cannot explain this variance, while some macroeconomic variables are able to capture the time-variation at least partly. I further show that volatility in exposures reduces the hedging effectiveness and leads thus to wrong decisions with regard to hedging activities. Trying to hedge an asset exposed to exchange rate movements can increase the variance of its returns rather than decreasing it.

1 Introduction

Swiss firms are strongly affected by exchange rate movements. This conclusion can easily be drawn when reading the business press headlines or official notes from politicians or business representatives. The reasoning behind this statement is that Switzerland as small, but economically strong country, is well-known for its export industry. Accordingly, the currency exposure is expected to be high.

A strong and fast appreciation of the Swiss franc (CHF), namely against the Euro (EUR) and the US-Dollar (USD) between 2010 and August 2011 (e.g. the CHF/EUR rate was around 1.50 on January 2010 and dropped to a minimum level of 1.03 in August 2011), has even led the Swiss National Bank to introduce a minimum exchange rate of 1.20 CHF/EUR on September 6, 2011. The main reason for this exceptional measure was an "acute danger for the Swiss economy" and a "risk of recession for the Swiss economy" according to the press release of the Swiss National Bank on September 6, 2011. It was not before January 15, 2015 that the Swiss National Bank discontinued to maintain this minimum exchange rate, bringing forward, amongst others, the argument that the "economy was able to take advantage of this phase to adjust to the new situation".

The study of Hutson and Stevenson (2010) supports the view of Swiss firm having a large exposure. They find Switzerland to be the country with the highest rate of firms with a positive exchange rate exposure (about 80% of Swiss firms are adversely affected by an appreciation of the Swiss Franc).[26] However, for a single firm it is not evident to know about its own exposure. Some evidence from a survey of Swiss firms in the 1990s can help to illustrate this. Loderer and Pichler (2000) have found that over 60% of the firms are not able to quantify their exposure[27], and over 25% did not even know whether

[26]A positive exposure means in this case that a firm benefits (suffers) from a depreciating (appreciating) home currency.

[27]Firms have been asked to indicate the impact of a ±10% change in various exchange rates on their operating cash flow.

unexpected currency rate changes would have a positive or negative effect on their cash flow.

The exchange rate exposure is thus a relevant research topic. In this study, I will investigate the exchange rate exposure of Swiss firms and especially focus my research question on how the exposure varies over time. Volatility in the exposure can be one important reason why firms have difficulties to estimate this risk. In a first step, I will thus estimate the exposure of listed Swiss firms and assess its time-variation at the firm level by means of a rolling regression methodology.

Second, I will explore whether the variance in the currency exposure can be explained by underlying firm-specific characteristics or macroeconomic conditions. This is relevant for understanding the volatility in the exposure and investigating its consequences. If the exposure level of a firm cannot be explained by firm characteristics, such as proportion of exported and imported goods, or by macroeconomic conditions, such as the gross domestic product (GDP) growth rate, the exposure itself can be seen as risky. This, in turn, can e.g. affect the hedging effectiveness of a firm, which leads to the third research question of this study.

Lastly, I will assess what the volatility in the exchange rate exposure implies in terms of hedging. This is an important aspect of why time-variation in the exposure matters. A manager of a multinational firm can hedge the exchange rate exposure of uncertain foreign currency future cash flows if he knows the (future) exposure. However, if the exposure is volatile, an effective hedging strategy is not possible anymore, because the estimation of the exposure from historical data does not exactly predict relevant (future) exposure. In the worst case, this deviation can even lead to counterproductive hedging, namely if the manager assumes a positive exposure due to observation of historical data, but due to its volatility, the actual exposure in the relevant (future) period turns out to be negative. This constellation, where the exposure has been positive in some periods and negative in other periods, has actually been observed in former studies about the time-variability of exchange rate exposures (see e.g. Jorion (1990), Brunner et al. (2000)).

The results suggest that exchange rate exposures of Swiss firms vary considerably over time and that firm-specific characteristics cannot explain the exchange rate exposure, while macroeconomic variables capture the time-variation at least partly. I show that the time-varying exposure reduces the hedging effectiveness. In some cases, this can even lead to an increased stock return variance for hedged positions compared to unhedged ones.

I contribute to the literature by investigating the effect of time-variation in exchange rate exposures on the hedging effectiveness and show that the hedging might actually increase the variance of stock returns instead of decreasing it. I further contribute to the literature by measuring the exchange rate exposure more precisely. Namely I measure the exposure against the most important currencies individually rather than with an exchange rate index and also consider the proportion of sales and assets in a particular region instead of just adding up all foreign sales or assets and compute their ratio to the total sales, resp. assets.

The paper is organized as follows. Section 2 provides a literature overview of exchange rate exposure in general and the time-variability of exposures in particular, section 3 explains the methodology and the econometric approach, section 4 provides the details about the data used in this study and section 5 presents the main results. Finally, section 6 explores the robustness of the main results and section 7 concludes.

2 Terminology and related literature

2.1 Definition of the exchange rate exposure and the exposure risk

The exchange rate exposure (or interchangeably the currency exposure) must first be distinguished from the exchange rate risk. The exchange rate risk simply measures the uncertainty about the future exchange rate, usually in terms of its standard deviation (or variance). The exchange rate exposure in contrast explains the sensitivity of a firm's financial position to unexpected movements in exchange rates, i.e. a large exposure means that a given exchange rate movement has a large impact on the firm's performance (Adler and Dumas, 1984). A first distinction in terms of exchange rate exposure can be made between the accounting and economic exposure[28]. The accounting (or translation) exposure measures how the firm's financial statements are affected by exchange rate movements, which is reflected in the cumulative translation adjustment (CTA). Only very few studies use the CTA as indicator of exchange rate exposure, one example is Shin and Soenen (1999).

A more common view is that the translation exposure as an accounting measurement does not affect the firm value, since under the assumptions of an efficient market, the firm value is the present value of all future cash flows. In this setting the economic exposure becomes relevant, which explains the effect of unexpected changes in the exchange rate on the firm's future cash flows and therefore on the firm value. The economic exposure can be further divided into the transaction and the operating exposure (Sercu and Uppal, 1995, p. 471). The former arises from contractual claims and obligations that are denominated in foreign currency and whose value in local currency will

[28]see (Sercu and Uppal, 1995, p. 471). However, the nomenclature is vague. Some authors refer to the economic exposure as operating exposure or classify the total exposure into direct and indirect exposure, such as Hutson and Stevenson (2010), where the direct (indirect) exposure refers to the transaction (operating) exposure. This article follows the denomination of Sercu and Uppal (1995).

depend on future exchange rates. Firms which purchase and sale products in foreign currencies are subject to this kind of exposure. The latter refers to the effect of changes in a firm's competitive position due to movements in exchange rates, such as changes in prices or costs, or if a firm's customers or clients use foreign currencies. An appreciation of local currency can thus be disadvantageous even for a domestic firm; frequently cited examples in Switzerland are the tourism industry (where the tourists from abroad suffer from high prices) or domestic retailers (where clients cross the near boarder for having shopping tours abroad).

The notion of exposure risk is different in a sense that it measures the volatility of the exchange rate exposure, i.e. how it varies over time. This differentiation is important for my study. While most research focuses on measuring the currency exposure, this study investigates the exposure risk. A firm with a constant exposure would not be subject to an exposure risk, whereas firms with a highly volatile exposure suffer from a higher exposure risk. I consider the exposure risk to emerge from random movements only. This follows the definition in Göx (2016), where the exposure risk is defined as part of the overall firm risk which is caused by the randomness of the firm's exposure to common risk factors, such as currency risks. If the volatility in the currency exposure can be explained by firm or industry-specific characteristics or by macroeconomic variables, one would thus not speak of exposure risk.

2.2 Literature overview of the exchange rate exposure

There exists a wide range of empirical studies measuring the exchange rate exposure of firms or industries. The foundation all of these investigations is the work of Adler and Dumas (1984). These authors measure the currency exposure as the regression coefficient from a regression of an asset, such as a firm's stock price, on the exchange rate.[29]

[29] The model will be described in more detail in section 3.1

Empirical investigations on the exchange rate exposure have found mixed evidence regarding the statistical significance. Even when the sample has been constructed on the basis of criteria indicating a high exchange rate exposure, only limited evidence in favor of a significant exposure has been found. For example, Jorion (1990) finds only a statistically significant exposure for 5.2% of the sample firms (at a significance level of 5%) even though he only considers internationally oriented U.S. companies. Similarly, Choi and Prasard (1995) select 409 U.S. multinationals with at least 25% foreign sales, net operating profit and physical assets, and find that no more than 61 of those firms (i.e. 15%) have a significant exchange rate sensitivity at a 10% level.

Research with non-U.S. samples has especially focused on strongly export-oriented countries, but with the same moderate success in identifying a significant exposure. He and Ng (1998) investigated a sample of 171 Japanese multinational firms and found 25% (2%) of the firms to have a significant positive (negative) exposure at a 5% level. Brunner et al. (2000) measures the USD exposure of German firms. They find 31% of the firms having a significant exposure coefficient at the 5% level using a model with orthogonalized exchange rate returns. Interestingly, the exposure varies substantially over the defined subperiods. The proportion of firms with a positive currency exposure is e.g. 71% in one subperiod, and in another subperiod this proportion drops to just 29%.

Bartram and Bodnar (2007) provide a comprehensive survey about empirical work on the exchange rate exposure. They summarize 31 studies and describe each with a short overview about the data, results and some methodological specifications. These studies differ in many ways. One aspect is the sample construction, where some studies focus on finding a sample that has a potentially high exposure, such as export-oriented firms or industries, while other studies select single countries or perform a global study. An important differentiation amongst the studies is made in terms of model design, e.g. about the control variables used or the way exchange rates are measured. Most models use a market return as control variable to control for macroeconomic effects that influence both stock returns and exchange rates. The choice of the market return variable can have a substantial effect on the results as shown by Bodnar and Wong (2003). In their study the authors compare value-weighted market portfolios with equally-weighted market portfolio as a control variable. They argue that value-weighted market-portfolio would put a higher weight on large firms which are more likely to be multinational and export-oriented and therefore also more likely to be positively affected by depreciating home currencies[30].

Most studies measure the exchange rate variable in the model using an index which is composed by a trade-weighted average of different currencies (Bartram and Bodnar, 2007). The potential benefit of using a bilateral exchange rate is generally acknowledged (see e.g. Doidge et al. (2006)), because using an identical exchange rate index for all companies is not necessarily representative for individual firms and can thus reduce the significance of the exposure estimates. But previous studies, such as Miller and Reuer (1998) have not found clear empirical evidence that using bilateral exchange rates improves significantly the results in measuring the exchange rate exposure and therefore, the majority of researchers sticks to the use of an index.

Researchers have as well used different methodological approaches. Nonlinear models, lagged variables or also time-varying exposures have all been examined. Empirical work on the temporal variation of exchange rate exposures will be further discussed later in this section.

Despite this diversity of empirical studies, only few among them have found a statistical significant exchange rate exposure for the majority of the firms. This has led to the situation known as the "exchange rate exposure puzzle" for which several possible reasons can be considered (Bartram and Bodnar, 2007). The most evident reason is probably the endogenous nature of the exchange rate exposure. Managers can hedge against exchange rate move-

[30]Bodnar and Wong (2003) find some empirical evidence to support this view. Other studies, however, argue differently by claiming that larger firms are more diversified and have therefore only small exposures, see e.g. Hutson and Stevenson (2010) or Pantzalis et al. (2001).

ments in order to adjust their exposure. I will further discuss this in the next subsection.

Another possible reason for low significance in many studies might be the use of the market return as control variable. If this control variable is included, the model does not measure the 'total exchange rate exposure' anymore, but rather the 'residual exposure', because the incorporation of the market return in the model also controls for the market portfolio's own exchange rate exposure (Bodnar and Wong, 2003). Depending on how strong the market itself is correlated with the exchange rate movements, the sign, size and significance of the estimates can be affected considerably. A strong correlation between those variables could lead to results which are not statistically significant, even for firms with a large exposure.

2.2.1 Exchange rate exposure and hedging

The degree to which a firm is exposed to exchange rate movements depends primarily on the imports and exports, its proportion of foreign to total sales, the currency denomination of its competitors, and the competitiveness of input and output markets of the firm's industry (Bodnar and Wong, 2003) or also on the openness of a economy in general (see e.g. Hutson and Stevenson (2010)). However, firms with a high sensitivity to exchange rate movements generally take measures to mitigate their exposure (Bartram and Bodnar, 2007).

Those measures can include financial as well as operational hedging activities. Some of the numerous possibilities to engage in operational hedging are described in this section. A first example is the geographical diversification, which is achieved if a firm has operations in more than one region with different currencies and the correlation between the exchange rates in those regions is less than one. For example, Pantzalis et al. (2001) use the number of reported segments as proxy for geographical dispersion, Allayannis and Ihrig (2001) use the number of countries in which a firm operates or Hutson and Laing (2014) classify the firm as domestic, regional, trans-regional or global depending on the number of regions in which the firm has activities.

Firms also differ in the extent they can impose exchange rate movements on the prices they charge to their customers in foreign markets. This effect of the exchange rate on the exporter's price in foreign currency is referred to by the term pass-through (Bodnar et al., 2002). A complete pass-through would allow a firm to change their prices in a way that there is no net exchange rate exposure left. This is of course very unlikely and the extent to which this is possible depends on several factors. Bodnar et al. (2002) establish a model in which the pass-through depends on the substitutability of the products and the market share of a company. In markets, where the products of the companies can easily be substituted, the pass-through is likely to be low.

On the other hand, the higher the market share of a company is, the higher is its power in the market and therefore the ability to increase prices in the foreign market if e.g. the local costs have increased due to an appreciation of the local currency. Bartram et al. (2010) extend this model and show how the pass-through can additionally depend on the competition of the input market[31]. Allayannis et al. (2001) generally refer to those factors as competitiveness of the input and final goods market. They claim that in oligopolistic market structures, the competition is less intensive and hence the markups are higher. Therefore firms can respond to exchange-rate fluctuations by altering the prices they charge and the exchange rate exposure is smaller compared to highly competitive market structures.

Another common operational hedging possibility is the adjustment of a firm's cost structure with respect to its revenues. If the costs of a firm incur in the same currency as the revenues, which can be achieved e.g. by choosing to purchase input factors in the same currency or by moving, resp. establishing production sites abroad, this will lead to a lower exchange rate exposure.

[31] Bodnar et al. (2002) model a market where a firm produces goods in its home country and sells them to a foreign export market and a foreign competitor, who produces and sells in the same market to which the first firm exports its goods. Bartram et al. (2010) extend this model allowing both firms to have costs and revenues both home and abroad.

Bartram et al. (2010) consider this possibility in their model and show that, ceteris paribus, a higher fraction of marginal costs in foreign currency reduces the exposure of export-oriented firms. This measure cannot fully eliminate the exchange rate exposure, since the profits as difference between the sales and the costs will still be measured in the foreign currency.

A firm can also raise debt in foreign currency, which has similar characteristics as sourcing abroad, except that in this case the financing costs are aligned to the revenues instead of the raw materials or the property, plants and equipment[32]. From an empirical point of view, the difficulty lies in the measurement of the costs, since they are not disclosed by segment. Bartram et al. (2010) as well as Gao (2000) use the percentage of foreign assets of a firm as proxy to measure the costs in foreign currency. For firms with production sites abroad, this proxy can be precise, for firms that produce locally but purchase raw materials in foreign currency, this proxy is less precise. Depending on the empirical approach, one must take care that the percentage of foreign assets can be highly correlated with the percentage of foreign sales. Doidge et al. (2006) find that foreign assets are positively related to exchange rate exposures and conclude that foreign assets might simply be a proxy for foreign sales. Therefore, regressing the currency exposures on the percentage of foreign assets might show a positive relation rather than a negative one.

A researcher who ignores the possibilities for hedging, will expect to find a high exchange rate exposure, e.g. for export-oriented firms. If the estimated exposure in his analysis is rather low (because the estimation measures the exposure after having considered all hedging activities), this result might at a first glance be surprising. But estimating a low exposure does in no way suggest that exchange rate movements are not important to firms, as already mentioned by Bartram and Bodnar (2007). Rather one should be aware of the difference between the 'gross' exposure (before any hedging activity) and the 'net' exposure (after having considered the pass-through and all hedging

[32]This kind of hedging activity is mostly assigned to the category of financial hedging together with the use of currency derivatives. Being just a matter of nomenclature, the categorization does not affect the size or the measurement of the exchange rate exposure.

activities).

Some studies further investigate the difference between the gross and net exposure, trying to measure the hedging activities of the firms and their impact on the exposure. Bartram et al. (2010) find that for the average firms, pass-through and operational hedging each reduces gross exposure by 10-15% and financial hedges (with foreign debt and currency derivatives) further decreases exposure by about 40%. Altogether, firms are able to reduce their gross exposure by around 70% through pass-through and hedging. The authors claim that the combination of these factors reduces foreign exchange exposures to the observed levels and is the main reason why previous researchers have struggled to find statistically significant exposures.

The literature on currency hedging generally assumes that the level of future foreign cash flows is known and the only risk is the uncertainty about the future exchange rate, i.e. the valuation of the future cash flow. Chen et al. (2003) provide an overview of hedging strategies which can be implemented in such cases. But given the factors described above, exchange rate movements do not only change the valuation of the future foreign currency cash flows, but also the amount of those expected cash flows.

A simple and descriptive example of such a situation, where both price and quantity about future foreign currency cash flows are uncertain, is given e.g. in Aabo (2015). An analytical analysis of a similar, but more complex situation, can be found in Kerkvliet and Moffett (1991). A perfectly effective hedge, which removes all risk from the future cash flow, is thus not possible and, in some cases, the hedging can even become counterproductive, e.g. by leading to worse lower-tail outcomes (Aabo, 2015). A relevant question is therefore, how these dynamics in exchange rate exposure affect the hedging effectiveness. This question will be addressed in section 3.4 in more detail.

2.3 The time-variation of the exchange rate exposure

There are several studies examining the time-variation of the exchange rate exposure. Already Adler and Dumas (1984) have mentioned that the exposure might vary over time and also the first empirical studies, e.g. Jorion (1990) have investigated this aspect. Mostly the time-varying exposure is not the main focus of the studies, but rather an addition to the main analysis. Since the volatility of the exposure can be highly relevant, this study will focus on the time-variation of the currency exposure.

One of the most common methods is to simply split the available time series data into different subperiods, as in Jorion (1990), Brunner et al. (2000), Williamson (2001), Bodnar and Wong (2003) or Parsley and Popper (2006). Within these intervals the exposure is then assumed to be constant and the exposure can therefore vary from one subperiod to another, but remains stable within each of the subperiods. This simple method can be adequate to gain some first insights about whether the exposure actually varies over time or not, but it remains difficult to amplify the analysis of the temporal aspect, since only few observations of exposures are obtained. Nevertheless those studies find considerable time-varying exposures.

Jorion (1990) as well as Brunner et al. (2000) even find evidence that the sign of the exposure varies between the subperiods. Jorion (1990) analyzes three subperiods (1971-71; 1976-80 and 1981-87) and finds that only 109 out of the entire sample of 287 firms exhibit the same sign for the exchange rate exposure in all subperiods. However, the standard errors are large and despite these findings the tests of stability cannot reject the hypothesis of constant exposures.

Brunner et al. (2000) create four subperiods and the length of the intervals depend on whether the USD has appreciated or depreciated against the German Mark (DM). Using both the standard model and a model with orthogonalized exchange rate returns, they find variation in the exposures over time. In subperiods of depreciation of the USD against the DM the exposure generally tends to be positive (meaning that the depreciation of the DM was interpreted favorably by investors and vice versa) and in the subperiod with a strong appreciation the measured exposures were mostly negative.

Parsley and Popper (2006) study the exchange rate exposure of Asian-Pacific firms and split their full sample into four equally long periods. In order to assess the time-variability, the authors include time dummies in the regression.[33] The results are then presented as percentages of firms within the sample which have a statistically significant exchange rate exposure at the 5% level. This method does not allow identifying how the sign of the exposure changes over time, but the percentage of significant exposure coefficients varies substantially. As an example, only 8% of Korean firms have a significant exposure in the period 1993-1995, compared to 70% in the period 1995-1997.

Another widespread approach to investigate the temporal aspect of exchange rate exposures is the use of a rolling regression in order to generate a higher number of exposure estimates. Brunner et al. (2000) for example regress daily stock returns over 250 days on exchange rate returns to estimate the exchange rate sensitivity and afterwards shift the interval by 30 days. Even though the periods are strongly overlapping, the results show a high variation over time in the exchange rate exposure. Similarly, Bodnar and Wong (2003) estimate the exposure with monthly data over a time horizon of five years and then shift the interval by one year. To further investigate the reasons why the exposure might vary, most studies use a two-step regression, where the estimated exposures of the first step are regressed on the determinants, which are expected to explain the exchange rate exposure.

For example, many studies use the ratio of foreign to total sales as determinant of the exchange rate exposure (see Bodnar and Wong (2003) for an overview). Other possible determinants are proxy variables for the hedging

[33]For each subperiod a time dummy is included interacting with the exchange rate return, thereby allowing a different regression slope per subperiod.

activities, such as the percentage of foreign to total assets, gross margin or the number of region in which the firm operates.

Other approaches explain the time-variability with macroeconomic factors rather than with firm- or industry-specific characteristics. They do so by using interaction of those macroeconomic variables with the currency exposure. Priestley and Odegaard (2007) model the exchange rate exposure as function of the exchange rate movements itself. Another example is Chaieb and Mazzotta (2013), who use a random coefficient model, where they interact the exchange rate movements with financial business-cycle indicators.

3 Methodology and empirical approach

3.1 Standard Model

In the finance literature one can already see on the basis of simple cash-flow oriented firm valuation models that movements in exchange rates will affect the cash flows and therefore alter the firm value. Based on this, the academic literature mostly defines the exchange rate exposure as the elasticity between changes in firm value and exchange rate measures.[34] Empirically, this exposure is obtained from an OLS regression of stock returns on exchange rate movements, as introduced by Adler and Dumas (1984):

$$R_j = \alpha_j + \sum_{i=1}^{n} \gamma_{i,j} X_i + \varepsilon_j \tag{54}$$

R_j is the stock return of the firm j, X_i represents the return on the ex-

[34]Only unexpected exchange rate movements are considered, since all expected changes are assumed to already be reflected in the asset's price. In accordance with previous literature, as e.g. Allayannis et al. (2001), I assume the exchange rate movements to follow a random walk process, therefore all changes in exchange rates are unexpected.

change rate of the Swiss franc against the currency i[35] and the regression coefficient $\gamma_{i,j}$ measures the (economic) exchange rate exposure. I use logarithmic returns for both the dependent and independent variable. In this case, $\gamma_{i,j}$ measures the percentage change of the stock return if the exchange rate moves by one percent.

In an efficient market setting, the firm value is an appropriate measurement for the exposure, since it reflects per definition the present value of all future cash flows. Movements in exchange rates affect these cash flows and have accordingly a direct impact on the firm value. However, when considering such a valuation method, one has to think about the impact of exchange rate movements on the discount rate. Bartram and Bodnar (2012) discuss how the currency exposure could already be priced in the asset by a risk premium. They find that the relation between the currency exposure and the firms' stock returns is more consistence with a cash flow effect rather than a discount rate effect and thus the impact of the currency movements on the discount rate is negligible.

Regression model (54) can serve as a benchmark and give a first idea about the exposure, but the model is not sufficiently specified, since a multitude of other factors affect stock returns and are also correlated with exchange rate movements, especially macroeconomic factors such as interest rates or inflation. Since Jorion (1990), almost all studies about exchange rate exposure add a market return variable R^M to the regression model to control for macroeconomic and general market factors. Thus, the model (54) can be extended to:

$$R_j = \alpha_j + \sum_{i=1}^{n} \gamma_{i,j} X_i + \beta_j R^M + \varepsilon_j \tag{55}$$

One has to be careful that the interpretation of the coefficient $\gamma_{i,j}$ has changed now. If the market return itself is also correlated with the exchange rate

[35] The exchange rates are computed as the home currency price of foreign currency, i.e. CHF/EUR, CHF/USD, etc. I explain the exact definition of all variables used in this study in appendix A.

movements, the exchange rate exposure $\gamma_{i,j}$ will be lower compared to model (54), since the incorporation of the market return in the model also controls for the market's own exchange rate exposure. Bodnar and Wong (2003) refer to the exposure in model (54) as the 'total exposure' and in model (55) as the 'residual exposure'. A residual exposure of $\gamma_{i,j} = 0$ does not mean that the firm j is not exposed to the exchange rate i, but rather that its exposure is the same as the market's currency exposure. The incorporation of the market return can be problematic if the market has a high correlation with exchange rate movements, because it would lead to a situation of multicollinearity. The consequences would be increased standard errors of the regression coefficients and estimates that are very sensitive to changes in the model.

There is also another potential problem of multicollinearity in the measurement of exchange rates. Most studies use an exchange rate index in their regression model rather than separating each currency as in (55). This index is usually trade-weighted, i.e. it is built on the basis of trade statistics of the respective country, giving more weight to currencies from countries with higher trading volume (see Bartram and Bodnar (2007) for an overview). The downside of this approach is that the same index is used for all firms, which does not reflect the economic reality. Firms operate in different regions to a greater or lesser extent and accordingly react differently to exchange rate movements in those regions. Many Swiss firms are strongly involved in the eurozone and thus I expect a high dependence on the EUR. Some firms are however more exposed to other currencies. For example, a firm like Swatch is more dependent on the exports to Asia than to Europe.

This study therefore uses the single currencies as regressors instead of a common index to all firms. Other studies like Makar and Huffman (2013), Parsley and Popper (2006) or Priestley and Odegaard (2007) have already used this approach. Parsley and Popper (2006) discuss the possible multicollinearity between the exchange rates, but come to the conclusion that it is not a serious issue in their study. I will as well discuss the correlations between the different currencies used in this study.

Additionally and thanks to the detailed information collected for this study, I was are able to create an individual exchange rate index for each firm, an approach which has rarely been used so far (see Makar and Huffman (2013)). This way I can combine the advantage of using individual currencies without facing the problem of multicollinearity. The most important currencies for Swiss firms with respect to foreign trade are the Euro (EUR) and the US-Dollar (USD). Asian currencies like the Hongkong-Dollar (HKD) have become increasingly important and will also be considered in the analysis[36].

More precisely, I define a firm-specific exchange rate index by weighting the currency returns in the index on the basis of the net sales in the corresponding region. For example, if a company generates more sales in the US, the USD receives a higher weight in the index. The index considers the EUR, USD and HKD and is defined as follows:

$$X_i^{index} = \sum_{j=EUR,USD,HKD} \frac{Net\ sales_{i,j}}{Net\ sales_i} * X^{CHF/j} \tag{56}$$

3.2 Time-variation of the exchange rate exposure

The models, which have been described so far, assume a constant exposure over the whole sample period. In this section I will introduce the time-variation of the exchange rate exposure. To do so, I divide the sample period T in several subperiods t and conduct for each subperiod separately the following regression:

$$R_{j,t} = \alpha_{j,t} + \sum_{i=1}^{n} \gamma_{i,j,t} X_{i,t} + \beta_{j,t} R_t^M + \varepsilon_{j,t} \tag{57}$$

Within the subperiods I assume the exposure to be constant. This is a

[36]During the year 2014, 45.8% of the Swiss exports went to the eurozone, 17.1% to Asia (resp. 3.3% to Hongkong and 3.0% to Japan) and 12.4% to the USA according to the statistical bulletin of the Swiss National Bank in June 2015.

key assumption for the use of this approach. As long as the exchange rate exposure is fairly stable during the subperiod, the simple OLS regression should produce unbiased estimates. The advantage of this non-parametric approach is that no assumptions about the functional form of the exposure or its determinants are required (Lewellen and Nagel, 2006).

The stability within a subperiod might appear to contradict the subject of the study at the first glance, but there are some good reasons why exposure can be seen as constant over a short time period. While the transaction exposure is rather a short term issue, the operating exposure is subject to slower and long-term changes (Hutson and Laing, 2014). The former can be hedged with financial instruments and there would accordingly be no or only a small influence on the stock price if exchange rates move. Changes in operational hedging activities, such as amending the cost structure, take more time, and the exchange rate exposure will adapt over time.

Imagine as an example a company which produces locally, i.e. in Switzerland, and sells primarily to the eurozone. A shock in the exchange rate CHF/EUR affects the company negatively and they experience negative stock returns in connection with this shock. As a consequence, the company decides to outsource some production activities to the eurozone as an operational hedging activity to align the costs with the revenues. The next time, when a similar shock in the exchange rate CHF/EUR occurs, this would not affect the company anymore, or at least to a lower extent.

I estimate regression model (57) by a rolling regression approach on a firm-level basis. The time series of estimated exposures generated by this procedure is then tested to evaluate whether the exposures remain constant over time. This will be done by running the following AR(1) regression model:

$$\widehat{\gamma}_{i,j,t} = \delta_{i,j}\widehat{\gamma}_{i,j,t-1} + \varepsilon_{i,j,t} \tag{58}$$

For constant exposures I expect the regression coefficient to be equal to one. Rejecting the hypothesis $\delta_{i,j} = 1$ would provide evidence for the presence of exposure risk. Another, more narrow approach would be to test whether $\delta_{i,j} = 0$ and conclude for all firms with a significant positive regression coefficient, that there is at least some stability over time. Either way, it will not be surprising to find a substantial time-variation in the exposure for some or even the majority of firms. The interesting questions arise subsequently to this analysis. First, I discuss whether the volatility can be explained by some observable variables or not. Second, I investigate whether the estimated, time-varying exposure is still useful for hedging purposes.

3.3 Determinants of the exchange rate exposure

In addition to the time-varying exposure, I assess if the volatility can be explained by firm-specific determinants or by business cycle indicators. One could directly test the determinants by interacting those variables with the exchange rate movements, which would be similar to e.g. Williamson (2001), Gao (2000) or Chaieb and Mazzotta (2013). An attempt to explain exchange rate volatility by business cycle indicators will be provided later in this section. Unfortunately, for firm-specific variables, the data is only available at a yearly basis, which makes this approach unsuitable, since it would limit the number of observations per firm to 16 for this study. With such a low number of observations, a possible time-variation in the exposure cannot be tested reliably. Thus, I will follow previous literature and implement a two-stage regression, where the estimated exposures of the first step are regressed on the firm-level variables in a second step.

3.3.1 Firm-specific determinants

As firm-specific determinants I will use the ratio of foreign sales to total sales $FS_{i,j}$ and possible hedging activities, such as in e.g. Gao (2000), Allayannis et al. (2001) or Hutson and Laing (2014). More precisely, I measure hedging activities with four different proxies. First, the geographical diversification DIV_j is measured by the number of regions that the firm operates in, counting all regions where at least 10% of the company sales are generated[37]. Second, I proxy the competitiveness of the firm by measuring the variable $MARGIN_j$ as EBIT divided by net sales. Third, the foreign production $FA_{i,j}$ is proxied by the ratio of foreign to total assets. And lastly, the financial hedging activities $FXD_{i,j}$ are measured by the contract value of outstanding currency derivatives as percentage of total assets. Taken together this leads to the following regression model, the subscript t is left out for simplicity:

$$\begin{aligned} \widehat{\gamma}_{i,j} &= \alpha_{i,j} + \delta_{0,i,j} FS_{i,j} + \delta_{1,i,j} DIV_j + \delta_{2,i,j} EBIT_j \\ &\quad + \delta_{3,i,j} FA_{i,j} + \delta_{4,i,j} FXD_j + \varepsilon_{i,j} \end{aligned} \tag{59}$$

The results can give some indication whether the variance of the exposure is driven by the determinants as measured above. Especially, a high R^2 would indicate that the volatility in the exchange rate exposure is not random, but largely determined by firm-specific variables. With respect to the expected signs one has to distinguish between net-exporters, which are expected to have an overall positive exposure, and net-importers, where the exposure is expected to be negative. For positive exposures I expect the coefficients of the determinants to appear as follows:

The sign for δ_0 is expected to be positive, meaning that firms with a high proportion of foreign sales should have higher exchange rate exposures. All other coefficients are expected to be negative, since a larger geographical diversification, more foreign assets, a higher EBIT margin or a higher contract volume of currency derivatives should, ceteris paribus, lead to a decrease in the exchange rate sensitivity.[38] For negative exposures, the situation is less evident, since most theoretical models and empirical studies focus on net-exporters. I expect the proportion of foreign sales to be positive and

[37] Four regions are distinguished: Switzerland, Europe/Middle East/Africa, Americas and Asia/Pacific.

[38] see section 2.2.1 for further details on the reasoning behind the expectation.

the proportion of foreign assets to be negative. Furthermore, I expect the geographic diversification and the use of financial derivatives to be positive.[39]

One should note that the foreign sales and assets are measured separately for each currency, as indicated by the subscript i, whereas the geographical diversification, the EBIT margin and the contract value of outstanding currency derivatives are obtained at the firm-level. Some firms disclose their EBIT for each segment or provide information about the currencies hedged by their financial derivatives. But this is only the case for few firms and in most cases not for the entire sample period. Hence, I cannot use this information for my study.

3.3.2 Macroeconomic variables

Chaieb and Mazzotta (2013) show that the time-variation of foreign currency exposure is driven by business cycle indicators and macroeconomic variables[40]. Following their study, I will examine the relationship between the foreign exchange rate exposure of Swiss firms to those factors by using the following random coefficient panel model:

$$\begin{aligned} R_{j,t} \quad = \quad & \alpha_{j,t} + \gamma_0 R_t^M + \gamma_0^{EUR} X_{EUR,t} + \gamma_0^{USD} X_{USD,t} + \\ & \sum_{k=1}^{K} (\gamma_k^{EUR} + \upsilon_{k,j}^{EUR}) IV_{k,t-1} X_{EUR,t} + \\ & \sum_{k=1}^{K} (\gamma_k^{USD} + \upsilon_{k,j}^{USD}) IV_{k,t-1} X_{USD,t} + \\ & \sum_{k=1}^{K} (\beta_k + \upsilon_{k,j}^{M}) IV_{k,t-1} R_t^M + \varepsilon_{j,t} \end{aligned} \tag{60}$$

[39] A geographical diversification will lead to an exposure closer to zero from any given exposure on. A change in the exposure from a strongly negative to a less negative one is a change with a positive sign and thus the regression coefficient for DIV_j should be positive. Analogous a firm with high negative exposure will use more financial derivatives to bring the exposure closer to zero.

[40] Chaieb and Mazzotta (2013) use default and term premium as business cycle indicators.

$IV_{k,t-1}$ represent the lagged macroeconomic variables, namely the gross domestic product (GDP) growth of Switzerland and the term spread (TS), which at several occasions has shown to perform well in predicting future macroeconomic conditions (Chaieb and Mazzotta, 2013). The term spread is defined as the difference between Swiss confederation bonds with 10-year maturities and the 3-month LIBOR for Swiss franc investments. A negative term premium indicates a downturn of the economy. γ_k^{EUR}, γ_k^{USD} and β_k are the average exposure coefficients, where statistical significance provides evidence that the variation in currency exposure is driven by the correspondent macroeconomic variables. $\upsilon_{k,j}^{EUR}$, $\upsilon_{k,j}^{USD}$ and $\upsilon_{k,j}^{M}$ are firm-specific deviations from those coefficients. The model is estimated by the maximum likelihood method as in Chaieb and Mazzotta (2013).

3.4 Hedging returns using the estimated exposure

There are several theoretical approaches to evaluate optimal exchange rate hedge ratios and also various ways of estimating them. One of the most widely used hedging strategy is based on the minimization of the variance of the hedged returns, where the so-called minimum variance (MV) hedge ratio is employed, see e.g. Chen et al. (2003). The return on a hedged asset is in this case given by:

$$R^h = R^u - h * X \tag{61}$$

where h is the hedge ratio and R^u the return of the unhedged asset. In a static setting without any volatility in the exchange rate exposure, the optimal hedge ratio h^* is given by

$$h^* = \frac{Cov(R^u, X)}{Var(X)} \tag{62}$$

which is the same as the estimated exchange rate exposure $\hat{\gamma}$ obtained in an OLS regression using model (54). In this case, the entire exposure can be removed and the variance of the hedged return is:

$$\begin{aligned} Var(R^h) &= Var(R^u - \hat{\gamma}X) \\ &= Var(\varepsilon) \end{aligned} \tag{63}$$

In a dynamic setting with time-varying exposure, one way to adapt the hedge ratio is to recalculate h based on the current information of the covariance matrix. The optimal MV hedge ratio at time t is then the regression coefficient $\hat{\gamma}_t$ given the information I at time $t-1$ (Chen et al., 2003):

$$h_t^* = \hat{\gamma}_t = \frac{Cov(R^u, X)|I_{t-1}}{Var(X)|I_{t-1}} \tag{64}$$

However, since the exposure based on conditional information, $\hat{\gamma}_t$, is an imperfect forecast for the realization of the exposure, γ_t, the variance of the hedged return is thus ex post not minimized.[41] Using $\hat{\gamma}_t$ as the hedge ratio leads thus to the return:

$$R_t^h = \alpha_t + \epsilon_t + (\gamma_t - \hat{\gamma}_t) * X_t \tag{65}$$

The exposure is now only completely removed if $\gamma_t = \hat{\gamma}_t$. Otherwise the variance of the hedged returns now also depends on the variance of the currency movements and the exposure itself. Following Göx (2016), $\hat{\gamma}_t$ is assumed to be a random variable with $N \sim (\gamma_t, \sigma_t^2)$ and $Cov(\hat{\gamma}_t, X) = 0$, the variance of the hedged return can be shown to equal

$$Var(R^h) = Var(\varepsilon) + Var(\hat{\gamma}) * (Var(X) + E(X)^2) \tag{66}$$

which is higher than the variance in (63) as long as $Var(\hat{\gamma})$ or $Var(X)$ is not zero. The expected exchange rate movement is zero, as explained in the previous section. The effectiveness of the hedging thus depends on the

[41] I refer to the realization of the exposure as the regression coefficient which would be obtained if all information of the relevant period could be used, e.g. if all data from 2014 is used to estimate the currency exposure of the year 2014.

variances of the exposure and the exchange rate. The higher they are, the higher will be $Var(R^h)$ and the lower will be the hedge effectiveness.

I construct a simple and descriptive example of an investor, who would like to hedge the exchange rate exposure of his investment, to illustrate the effect of a time-varying exposure on hedge effectiveness. Taking the actual data from the firm 'Jungfraubahn Holding AG', I find a significant exposure of 1.04 against the Euro for the years 2008-2009, a significant negative exposure of -1.03 for the years 1999-2000 and an exposure close to zero for the years 2012-2013. These estimates will serve as the realized exposures γ_t.

I use the company 'Jungfraubahn Holding AG' for this example, because I can find both, significant positive and negative exposures for this company during the sample period, which suggests some time-variation in the exposure. Additionally, this company has only very limited possibilities to operationally hedge its exposure, since as an operator of excursion railways and provider of winter sports facilities, its assets are geographically tied to Switzerland and there are no possibilities to export these goods. Nevertheless one can expect a significant exposure to foreign currencies, since the majority of its customers are tourists from abroad.

For the three exposures estimated at the different points in time described above, I compute the weekly, hedged returns as shown in (61) over a time horizon of two years, e.g.

$$R^h_{2008-2009} = R^u_{2008-2009} - h * X_{2008-2009} \tag{67}$$

This leads to 104 observations, for which the variance, resp. the standard deviations are computed and shown in the table below. I arbitrarily use the hedge ratios $\{-1, 0, 1\}$ and compare the standard deviations of R^h. One can see that the lowest standard deviation always occurs when the 'correct' hedge ratio has been used, i.e. the same as the realized exposure. In the other cases, using a wrong hedge ratio even increases the variance compared to the unhedged return. For example, in the years 2008 and 2009, when the unconditional estimation has shown a realized exposure of 1.04, an unhedged position would have led to a standard deviation of 0.03673. Wrongly applying a hedge ratio of -1 would have led to a higher standard deviation of 0.04035.

[please insert table 9 about here]

Volatility in the exposure, which causes differences in the applied hedge ratios and the realized exposures, thus affects the effectiveness of the hedging and a high volatility can even be counterproductive, meaning that the variance of the hedged return turns out to be higher than it would have been without any hedging, i.e. $Var(R^h) > Var(R^u)$.

A possible measure for the effectiveness of the hedging is to compute how much variance has been removed by the hedge procedure. I thus define the hedge effectiveness as follows:

$$Hedge\ effectiveness = \frac{Var(R^u) - Var(R^h)}{Var(R^u)} \tag{68}$$

A positive number means that the hedge successfully reduced the variance of the returns compared to the unhedged ones. In the extreme case, a hedge effectiveness of 100% indicates that all variance has been removed and the hedged returns are constant. 0% indicates a completely useless hedge and a hedge effectiveness below 0% reveals a counterproductive hedging.

I used the example of an investor, who would like to protect his investment from currency movements, because it is comprehensible and this empirical study is based on stock returns. The basic principle is a situation of future foreign cash flows, where there is not only uncertainty about the exchange rate, but also about the amount of cash flows. The exposure risk arises from this twofold uncertainty and prevents perfect hedging.

The same concept can easily be transferred to other settings. One can imagine for example a manager of a multinational company who would like to hedge dividend payments of the firm's European subsidiaries to its headquarter in Switzerland against exchange rate movements. Instead of just naively hedging the amount of expected dividends ($h = 1$), the manager can estimate the more sophisticated hedge ratio $\hat{\gamma}_t$ based historical data. However, as described above, the effectiveness of this hedge will depend on the volatility of the exchange rates and the exposure $\hat{\gamma}_t$.

4 Data

The basic population for this study contains all firms listed in the Swiss Performance Index (SPI) as per end of 2014[42]. I exclude different categories of firms. First, banks and other financial institutions are not considered, mainly because the exchange rate exposure is part of their daily business and it is expected that they manage those risks in a different way than non-financial firms. This restriction is consistent with most other previous studies on the exchange rate exposure. Second, firms with headquarters outside of Switzerland are excluded as well as firms which report their financial statements in a foreign currency. A necessary condition for a Swiss company to be allowed to choose a functional currency other than the Swiss franc, is that sales and costs must mainly be generated in that other currency. Third, firms with less than five years of consecutive data of stock returns are excluded and lastly some very illiquid firms are removed (as e.g. in Brunner et al. (2000))[43]. In cases where the same company has two different types of shares listed in the stock exchange (e.g. Swatch transferable and personal share), only one type of share is kept in the sample. Out of the 209 listed companies in the Swiss Performance index as per December 2014, the sample used for this study

[42]The SPI® contains over 200 stocks, which is the vast majority of all listed companies at the SIX stock exchange in Switzerland and is considered to be Switzerland's overall stock market index.

[43]More precisely, I exclude a firm if the average annual trading volume over the sample period is less than 5% of the outstanding stocks.

contains exactly 100 companies after all exclusions.[44]

I extract the market and firm-level data from Datastream. The market data I use are the different exchange rates and returns of the SPI. The firm-level data I use are the stock returns (measured as total shareholder returns), accounting measurements (net sales, EBIT, total assets), geographical information on sales and assets and the contract value of foreign exchange derivatives. The geographical information allows to allocate the sales and non-current assets of a whole firm to the regions in which the firm is active.

However, there are some measurement problems related to this information. Before 2009, IAS 14 was the relevant accounting standard on segment reporting. It required firms to report details on business and geographical segments. Sales and non-current assets had to be reported for both kind of segments, but more detailed information, such as the operating result, had to be disclosed only for the primary segment, but not for the secondary segment. The operating result per region would have been an interesting information source for this study but since only few firms use geographical segments as primary segment, there is little data available on segment results.

The introduction of IFRS 8 for annual reporting periods beginning in 2009, has led to some differences in the segment reporting. Since 2009, only one reportable segment was required to be disclosed. If geography is not the reportable segment, some geographical information has to be disclosed as entity-wide information. In this case, firms need to disclose sales and non-current assets of single countries, but not for a whole region. This can lead to situations, where e.g. a firm first included the sales in Switzerland in the segment 'Europe', but since 2009 disclosed those sales separately.

Furthermore, the segments can change over time. For example, a firm might have summarized the region Asia in the segment 'Rest of the world' for some periods. But due to the strong growth in this region, the firm needed to cre-

[44]The large reduction of the sample size is mainly due to the numerous financial institutions which have been excluded.

ate a separate segment for this region later on. Lastly, firms applying Swiss GAAP FER have less extensive disclosure requirements, e.g. they are not required to report segment assets.[45] Because of the variety of possible disclosure on geographical information, the available date from Datastream had to be manually assigned to the respective regions and in many cases has been cross-validated with the annual reports to remove existing inconsistencies and ensure the accuracy of the data.[46]

The sample period contains data from January 1999 until December 2014. A longer period would lead to some conceptual problems, since the Euro was introduced in 1999 and by using data before 1999 I would need to consider a variety of different European currencies. The exchange rate and stock returns are measured as weekly, logarithmic returns. The interval of one week is a compromise between the advantages of a longer period, which are less prone to the daily, random fluctuations in stock prices and the advantages of a shorter interval, which provides more data. Previous literature has often used monthly return data, see e.g. Allayannis et al. (2001) or the discussion in Lewellen and Nagel (2006), but weekly data is as well a common interval, e.g. as in Bartram and Karolyi (2006) or Dominguez and Tesar (2006).[47]

4.1 Sample description

Table 10 shows the descriptive statistics of the variables used for regression models (1)-(3) and also for the determinants of the exchange rate exposure used in (5) and (6). For the exchange rate returns, the stock and market returns, 834 observations are available, which corresponds to weekly data over 16 years. With respect to the EUR, one has to be aware that the

[45]FER 30.42 requires the disclosure of net sales per geographical market. FER 31.8 requires the reporting of sales and earnings per operating or geographical segment.

[46]For example, some firms report their segment revenues based on production site and customer location separately. In this case, I ensured that always the sales based on customer location was assigned to my data set.

[47]In section 6 it is shown that the choice of the interval does not change the results of the study.

Swiss National Bank had introduced a minimum level of 1.20 CHF/EUR on September 6, 2011 and has maintained that level until January 15, 2015. The interval from September 2011 until December 2014 has therefore only small fluctuations and the observed exchange rate is not the one which would have been observed in a free market without the intervention of the National Bank. This has no negative impact on my investigation, however, one can only state that during this period the stock return movements cannot have been caused by exchange rate fluctuations and due to the small variation in exchange rates, one can hardly measure any correlation between those variables.

[please insert table 10 about here]

The variable $FS_{Switzerland}$ is the ratio of the sales in Switzerland to the total sales of the firm in a year. The average company generates 25.5% of their revenues in the domestic market, 43.1% in Europe, 15.6% in Northern America[48] and 11.0% in Asia. The minimum level is zero for all currencies and the maximum level ranges from 0.71 to 1.00, showing the large dispersion of sales and that using the same currency index for all firms would not be appropriate to measure the exchange rate exposure of Swiss firms.

The variable *FXD* shows the percentage of the contract value of outstanding currency derivatives in terms of total assets. This proxy for financial hedging has been used amongst others by Allayannis et al. (2001). More than 25% of the firms explicitly mention that they have no open currency derivatives in the year of measurement. In terms of diversification, the average firm has significant sales in more than 2 regions, mostly Switzerland, Europe and/or the Americas. All variables, except of the raw exchange rates, are winsorized at the one percent level to mitigate the effect of outliers.[49]

[48] some firms report both Northern and Southern America in one segment. In that case no separation was possible and the whole segment sales have been attributed to Northern America, assuming that a large majority of the sales would have occurred in the USA.

[49] All regressions and analysis are also conducted with the original data. The results are virtually the same. However, the R-squared are usually slightly higher with the winsorized variables.

The EBIT margin is additionally limited to zero to preclude some obvious errors in the data.[50] The logarithmic GDP growth rate is available on a quarterly basis and the information is obtained from SECO (State secretariat for economic affairs). To align the data frequency, I measure the term spread as well at a quarterly frequency, the source of this information is the SNB. There are two observations with negative term spreads, which are supposed to indicate a downturn in the economy, the first one occurred in the second quarter of 2001, and the second one in the fourth quarter of 2008.

A possible multicollinearity of the exchange rate returns could be a problem for the regression approach used in this study. In table 11 I thus show the correlation coefficients between the currencies used and also between the market return for the weekly returns over the entire sample period. One can see that there is a certain correlation between the returns of the EUR and USD, resp. the HKD, but this will most likely not be an issue of multicollinearity in the study. However, the correlation coefficient of 0.91 between the USD and HKD is in my view considered as an issue and I therefore skip the HKD when estimating the exchange rate exposure.[51]

[please insert table 11 about here]

I also investigate the correlation coefficients between the variables for the foreign sales and asset percentages, because one might expect that e.g. the percentage of sales to the US is highly correlated with the assets of that company in the US. But the coefficients range from 0.47 (Asian sales and assets) to 0.65 (Swiss sales and assets), the details are provided in appendix B. Thus, I will include both variables, *FS* (foreign sales) and *FA* (foreign assets), as regressors in the same regression. In the cases where I use the firm

[50]Not restricting the EBIT margin would lead to some important outliers (even after winsorizing at the 1% percentile), since often the newly listed companies with few sales still experience losses. All negative values are thus replaced by zero.

[51]Using HKD instead of USD leads to very similar results for the regression, which is not surprising regarding the high correlation between those two currencies.

specific index, I will again include the HKD, since multicollinearity would not be a problem in that case.

4.2 Descriptive statistics on the estimated exposures

I briefly present the summary statistics of the estimated exposures. Table 12 shows the average regression coefficient per industry and per currency from regression model 57, i.e. from the rolling regression approach.

[please insert table 12 about here]

Overall, there are no particular differences between the industries. Only the telecommunication sector shows a more pronounced deviation from the mean, since it is the only sector with a negative exposure to the EUR and a positive one against the USD (together with the technology sector). But this industry just contains one single firm in my sample and might thereby not be representative for the whole sector, even if the very low exposures are not surprising regarding that the telecommunication industry is a very local business with few international activities. Other industries, which seem to have low currency exposure, are e.g. the consumer goods and the utilities sector, while technology or industrials firms have on average higher exposures.

5 Results

5.1 Results of the standard model

On the basis of models (54) and (55), I first estimate the exchange rate exposure with a pooled OLS regression over the entire sample period. The results are reported in table 13. They show a significant regression coefficient for the exchange rate movements of the EUR and USD, both in model (54) and in model (55), when taking into account the market return. For example, a one percent increase in the exchange rate CHF/EUR is associated with an .92% increase in the stock return when using model (54). When controlling for the market, this coefficient drops to .27%.

Interestingly, there is a negative regression coefficient for the USD, meaning that the average Swiss firm experiences positive stock returns when the CHF appreciates against the USD, even when controlling for the market return. However, in third column I regress the stock returns on $X^{CHF/USD}$ only and one can see that the exposure is positive in this case. Otherwise the coefficients remain stable. For example, the estimate for the market return is always between .69 and .73 and significant at the 1%-level.

[please insert table 13 about here]

A glance at the coefficient of determination shows that the exchange rate returns can hardly explain the stock price movements of the companies. Adding the market return to the regression improves the coefficient of determination, but the R^2 remains at a low level of around 10%.

The fourth and eighth column uses the firm-specific exchange rate index X^{index} as independent variable. I find a positive significant exposure when using model (1), but no significant positive coefficient when controlling for the market return. This result suggests that a foreign exchange index might not be able to identify significant currency exposures in contrast to the single currencies.

In a next step the regression models (54) and (55) will be conducted for each firm separately. This firm-by-firm regression approach allows to get an impression of how relevant the exchange rates are to the single companies and for how many firms the stock returns are positively and negatively related to e.g. an appreciating Swiss franc. I present the results in table 14.

One can see that the Euro plays an important role for Swiss firms. Around

86% of the firms have a significant exchange rate exposure to the Euro. When controlling for the market return, this level shrinks to 24%. Most firms have a positive exchange rate exposure to the Euro, i.e. a higher exchange rate CHF/EUR is associated with positive stock returns. Yet, whereas in model (54) almost all firms had a positive regression coefficient for the EUR, in model (55) just 82.0% of the coefficients were positive. With the different interpretation of the coefficients for model (54) and ((55) in mind, the explanation for that difference is evident.

In model (55), $\gamma_{i,j}$ measures only the residual exposure. Thus, firms who had a low, but positive exposure in model (54) will exhibit a negative exposure in model (55), because the market return itself is positively related to the exchange rate returns. The exposure against the USD is again negative, which confirms the results of the pooled OLS regression. 66.0% of the firms have a negative coefficient, resp. even 80.0% when controlling for the market return. In the case where the firm-individual exchange rate index is used as independent variable, 57.0% of the firms show a significant exposure in model (54) and only 7.0% in model (55).

[please insert table 14 about here]

These results are similar to many other studies on the exchange rate exposure, especially when the sample consists of firms in export-oriented countries like Switzerland. Dominguez and Tesar (2006) as an example find significant exchange rate exposure at a 5% level for up to 21.5% of the firms in export-oriented countries like Netherlands or Japan using a trade-weighted index. Similarly, Hutson and Stevenson (2010) find significant exposures for 7.8% of Swiss firms.

5.2 Results on the determinants and the time-variation of the exchange rate exposure

In this section, I will use regression model (57) to estimate the currency exposures by a rolling regression approach, where firm-by-firm regressions are run over a time horizon of two years. The first regression covers the period 1999 to 2000 and contains 104 weekly observations. Then the interval is shifted forward by one year after each regression, until the last interval, where the sample period is 2013 to 2014. Thereby I obtain 15 different exchange rate exposure estimates γ_i for each firm j.[52] Table 15 shows the results of these regressions to check the consistency of the outcome with the results in the previous subsection.

[please insert table 15 about here]

As the previous results suggested, also on a firm-level basis the Euro plays an important role for most companies. 39.7%, resp. 10.3% of the companies have a significant exposure against the EUR, the vast majority of coefficients are positive. Regarding the exposure towards the USD, again more companies have a negative exposure. The overall mean of the exchange rate exposures are found to be .3703 for the EUR (with a standard deviation of 1.0599), resp. -.0904 (.4535) for the USD as one can see in table 12.

In order to get a better picture of the volatility of the exposure, I will analyze the obtained exposure estimates on a firm-level basis. A first impression on the stability of the exposures against the EUR is given in figure 1, which shows the development of the currency exposures over time per industry.[53] One can see that for all industries the exposure has changed at least once from positive to negative or vice versa during the sample period.

[52] For some firms, data is not available for the entire sample period from 1999 to 2014 and accordingly there will be less than 15 exchange rate exposures for some firms.

[53] Plotting the same graph using the exposures against the USD leads to similar patterns with more industries having negative coefficients.

[please insert figure 1 about here]

For hedging purposes, it is especially harmful, if one assumes or estimates a positive (negative) exchange rate exposure based on historical data, but it turns out that the actual exposure for the relevant period is negative (positive). In this case the hedging activities would be counterproductive, as discussed in section 3.4. The constellation of changing signs appears in my sample more frequently than expected. Using the estimated firm-level exposures as shown in table 15 (model (55)), I obtain 376 changes in signs for the exchange rate exposure against the EUR and 393 for the USD.[54]

For comparison, I also computed the number if sign changes for the regression coefficient of the market return β_j. This coefficient is much more stable, with only 66 changes in signs. On average a company experienced thus more than three changes in signs of the exchange rate exposure both against the EUR and the USD during the period from 2000 to 2014. These numbers refer to all estimated coefficients, not only the significant ones. Accordingly, some changes in signs might just occur because the exposure moves around zero without any statistical significance and one has to be careful when interpreting these results.

If one only considers the significant exposures, the number of changes in signs is small. This is due to the low number of significant exposures. For example, I estimated 142 (146) significant exposures against the EUR (USD). Among these estimates, there have only been 12 (13) changes in sign. For a single firm, it happens thus rarely that the exposure is both significantly negative and positive during the sample period. More often the coefficient moves from a significant to a non-significant exposure.

[54]For the EUR, out of the 336 sign changes 200 went from positive to negative and 176 from negative to positive. For the USD, out of the 393 sign changes, 199 went from positive to negative and 197 from negative to positive.

5.2.1 The time-variation of the exchange rate exposure

section 3.2 describes one way to more formally assess the volatility of the estimated currency exposures. I will now estimate regression model (58) on a firm-level basis and use a Wald test to determine whether the regression coefficient $\delta_{i,j}$ is significantly different from one. Rejecting the hypothesis $\delta_{i,j} = 1$ would suggest a considerable time-variation, i.e. that the exposure at time t is significantly different from the one at time $t-1$. As an alternative, I test $\delta_{i,j} = 0$ as well. Not rejecting $\delta_{i,j} = 0$ would be even a stronger evidence for time-varying exposure, though it is more difficult to interpret, since it is not a necessary condition for time-variation. Firms with low, but statistically significant regression coefficient $\hat{\delta}_{i,j}$ can still be prone to a time-varying exposure.

I now use regression model (58), where I regress the exposure at time t on the one at time $t-1$. The results shown in table 16 indicate that there is a significant volatility in the exchange rate exposure for many firms. The average regression coefficient is .5048 for the EUR and .4676 for the USD, which might suggests that the exposures at time t can at least partially be explained by its estimate at $t-1$. Looking at the firm-level results and testing for $\delta_{i,j} = 0$, one can identify that in many cases the regression coefficient $\delta_{i,j}$ cannot be distinguished from zero. For the exposure against the EUR, 41 (59) out of the 100 firms show a p-value higher (lower) than .05. For those 41 firms, the exposure against the EUR (USD) at $t-1$ provides no information on the exposure at time t.

[please insert table 16 about here]

Testing whether $\delta_{i,j} = 1$, the hypothesis is rejected for 67 (67) out of the 100 firms at a p-value of .1 when looking at the exposure against the EUR (USD). Requiring a p-value below $p = 0.01$ makes it more difficult to reject the hypothesis $\delta_{i,j} = 1$ and leads to a rejection of only 27, resp. 26 firms, for which the exchange rate exposure in time t is significantly different from the one at $t-1$.[55] The average R^2 is .32 for the EUR and .29 for the USD, but the coefficients of determination are highly dispersed across firms with values ranging from .00 up to .94.

Depending on the time horizon and especially on the regression interval that have been employed when estimating the exposures, the results of regression (58) will be different. For highly overlapping estimation windows, the exposures will not vary much from one period to another. Hence, in those cases the autocorrelation is higher than it would be with non-overlapping intervals and it becomes more difficult to reject $\delta_{i,j}=1$. Section 6 will address this sensitivity in more detail.

5.2.2 Firm-specific determinants of the exchange rate exposure

This section aims to explain whether the volatility in the exposure can be explained by firm-level characteristics. For this purpose, I run regression model (59) separately for both currencies and also for positive and negative exposures.[56] Regression (59) takes the estimated exposures from the previous step as dependent variable and firm-specific variables as independent variables. A firm-level analysis is not appropriate anymore, since the determinants can only be measured on a yearly basis, which gives not more than 15 observations per firm. Additionally, there is some missing information due to different disclosure requirements with respect to time or the applied accounting standards. Hence, a pooled regression will be run for analyzing the determinants.

The results in table 17 can give an insight how firms might manage their exposure and which hedging activities are used by firms with high, resp. low exchange rate exposure. While this second step regression analysis is

[55] There are no firms with an estimated regression coefficient bigger than one for which $\delta_{i,j}=1$ is rejected, meaning that all those 27, resp. 26 firms have a $\delta_{i,j}$ significantly lower than one.

[56] The reasoning behind that is the different expectations for the signs of the coefficients as discussed in section 3.3.1

common in many studies about the exchange rate exposure (Bartram and Bodnar, 2007), one has to be careful with its interpretation. Since the estimated coefficient $\hat{\gamma}_{i,j}$ reflects only the post-hedging exposure, a low currency exposure can result from both, a low operational exposure or a higher one, which has been significantly reduced by hedging activities (Bartram and Bodnar, 2007). Furthermore, due to the endogenous nature of the firm-specific variables, the regression coefficients show associations of those variables with the exposure, but no causal claims can be made on how the firms react to changes in their exposure.

[please insert table 17 about here]

Overall, there seems to be little evidence that hedging activities significantly reduce the exchange rate exposure. The only significant coefficient for the positive exposures is the EBIT margin, indicating that firms with a high positive currency exposure have on average a lower EBIT margin. The foreign sales show a positive coefficient and the foreign assets show a negative one, but the coefficients are not statistically significant. Similarly, the coefficients for the diversification variable and the financial hedging cannot be distinguished from zero.

Regarding the negative exposures, the diversification seems to provide some protection from the exposure, i.e. a higher diversification is associated with an exposure closer to zero. The coefficient of .1075 is significant at the 5%-level. The ratio of foreign sales shows a negative coefficient. This is against the prediction, since at any level of exposure, I expect that an increase in foreign sales would be associated with an increase in the exposure.

The coefficient for the currency derivatives is mostly negative, but never significant at a 5%-level. While the expectation is to have a negative coefficient, and some studies (e.g. Allayannis et al. (2001)) indeed find evidence that exchange rate exposure decreases with the use of financial derivatives, other studies actually find positive coefficients (e.g. Pantzalis et al. (2001), and the authors' interpretation of this finding is that highly exposed firms might choose to use more currency derivatives to mitigate their risk.).

An interesting finding is that the proportion of variance that can be explained by the hedging activities is very low, the R^2 being only between .026 and .070. This means that a substantial part of the variance in the exchange rate exposure cannot be explained by the model. Similarly, previous studies have found a low explanatory power when investigating the determinants of the exposures, mostly below 15% (see e.g. Doidge et al. (2006), Gao (2000) or Hutson and Laing (2014)). This supports the view that the exchange rate exposure moves randomly, because there are movements over time, but those movements cannot be explained by changes in hedging activities.

5.2.3 Macroeconomic determinants of the exchange rate exposure

The next step will provide results on whether the volatility of the currency exposures can be better explained by macro variables rather than firm characteristics. The quarterly available data now allows to directly estimate this relationship by using the mixed-effects linear regression model (60). Firstly, and closely related to Chaieb and Mazzotta (2013), I confirm that the currency exposure is still significant and time-varying despite of using another model.

[please insert table 18 about here]

There is again a significant positive exposure of the average firm against the EUR and a significant negative exposure against the USD. The significance of the interaction terms confirms the time-variation of the exposure. A constant exposure might lead to a significant coefficient $\hat{\gamma}_0$, but would not show significant interaction terms $\hat{\gamma}_1$ or $\hat{\gamma}_2$. Furthermore, the results not only confirm the volatility, but also suggest that the time-variation is driven by macroeconomic variables. Against the EUR, both the GDP and TS have a negative coefficient. This implies that the firms are less sensitive to exchange rate movement in times of economic prosperity, respectively a negative shock in the time spread or GDP growth is associated with higher exposures in the following quarter.

Taking the EUR and the term spread as an example, the economic interpretation of the coefficients is as follows: The unconditional exposure is 1.89 and thus, a decrease of one standard deviation in the term spread is (using the coefficient $\hat{\gamma}_1$ of -1.05 and the standard deviation of the term spread (.7036)) associated with an increase in the exchange rate exposure from 1.89 to 2.63.

The results do not change significantly if both currencies are used in the same regression or if the exposures is estimated separately for each currency. The findings are consistent with the general conclusion in Chaieb and Mazzotta (2013), where the currency exposure tends to be higher during economic contractions.

5.3 Hedging returns using the estimated exchange rate exposure

The results so far suggest at least some volatility of the exposures. I will now investigate the possible consequences of the time-variation in exchange rate exposure. To do so, I estimate the yearly variances of the raw stock returns for each firm and compare them to the variances one would get by hedging the stock returns as suggested in (61).

Table 19 shows the results of this comparison. Each of the four large columns contains the average variance of the unhedged positions R^u and the hedged positions R^h. It as well presents the percentage of the variance, which has been filtered out by the hedging, i.e. a positive number indicates that the hedging was able to reduce the variance of the returns compared to the unhedged stock returns.

R^u is simply calculated as the yearly variance per firm of the weekly stock returns. The table then shows the aggregated average variance. For example, .00188 is the average variance of all years and all firms in the basic material industry.[57]

[please insert table 19 about here]

The column R^h computes the variances of the hedged returns. More precisely, I estimate the exposure over a certain time horizon, e.g. using the data from 1999 to 2000, and then use the estimated exposure $\hat{\gamma}_{2000}$ as hedge ratio for computing the variances of hedged returns as in equation (61). For the ex post hedging, the returns of the year 2000 are hedged by using $\hat{\gamma}_{2000}$. This approach is equivalent to an in-sample-prediction, since I use all information in a particular year to hedge the exposure in the same year. This is, of course, not possible in the real world, but it can be seen as a benchmark solution.

Realistically one can only use the estimated exposure to hedge against future exchange rate movements, which is simulated in the other large columns. In these cases, the approach corresponds to an out-of-sample prediction. For the same estimated exposure as before, i.e. $\hat{\gamma}_{2000}$, I now compute the hedged variances of the stock returns in the year 2001 (one-year-ahead), 2002 (2-years-ahead) and 2003 (three-years-ahead), respectively. A time horizon of one year is realistic and commonly used in the literature and in practice. The three year time horizon might seem too long, but it can help to understand the consequences of trying to hedge time-varying exposures. Again, the variance is estimated per year and for each firm separately and the numbers in table 11 show the average of all those variances.

Compared to the unhedged returns, the ex post hedging is able to reduce the average yearly variance of the stock returns by 3.63%. This is logical,

[57] The reason why R^u is not identical in all four large columns is that the number of years used to calculate R^u is not the same in each large column. For example, the ex post hedging computes variances for the years 2000 to 2014, but for the 3-year-ahead hedging, the data of R^h is only available from 2003-2014, and hence, I use this period to compute R^u as well.

since the in-sample-prediction produces the best results by construction. The industry, where ex post least of the variance has been filtered out, is the consumer goods industry with a variance reduction of 2.41%, but the results are similar across industries.

If there is no exposure risk at all, then the hedging would be equally successful, no matter what time horizon is used. Regarding the results about exposure volatility in the previous subsection, it is not surprising to see that the hedging becomes less effective the longer the forecasting horizon is. Even when using the estimated exposures to hedge the stock returns just one year ahead, the variance of these stock returns is higher by .30% compared to the unhedged position, meaning that not hedging the stock returns would have led to a smaller variance. An interval of three years shows an increase in variance for all industries except utilities and technology.

The results suggest that there is a serious exposure risk which can lead to wrong decision-making. Due to the time-varying nature of the currency exposure, the estimates generated from past information should not carelessly be used for hedging the exchange rate exposure. The longer the forecasting horizon is, the greater is the risk of counterproductive hedging.

6 Robustness checks

In this section, the robustness of the empirical results will be addressed. Overall the results do not alter substantively and are thus robust to different specifications.

6.1 Time horizon and intervals

For all analyses so far, the exchange rate exposures have been estimated over a time horizon of two years with weekly data. The weekly data has been a compromise between the advantages of a longer period, which are less prone to short term random fluctuations in stock prices and the advantages of a shorter interval, which provides more data. The time horizon of two years has been chosen in order to obtain enough data without using too old data, which might be irrelevant for estimating current exposure. I will now recompute the results with different time horizons, namely one, two and three years of data for the weekly returns and three, four and five years for the monthly data. Another choice in the empirical approach consists of the interval used for the rolling regression. Throughout the paper, an interval of 12 months has been used between two regressions. In this section I will also present the results for an interval of 6 months.

The proportion of firms with significant exposures against the EUR and the USD at the 5%-significance level has been 10.3%, resp. 10.6%. For all kind of different specifications with respect to time horizon, data frequency and regression interval, this proportion remains between 9.2-10.9% for the EUR and 9.9-11.2% for the USD. These narrow intervals show that the overall proportion of firms with significant currency exposures is robust to the different model specifications.

The volatility of the exposures does not significantly depend on the time horizon or the data frequency used, but it is comprehensible that the regression interval has some effect on the results of the volatility as shown in the table 20. A shorter intervals means a higher overlapping, especially when longer time horizons are used. Hence, $\delta_i^{EUR} = 1$ can be rejected only for 26 out of 100 firms when using a time horizon of three years and an interval of six months, but for 88% of the firms when the time horizon and the regression interval is one year (in which case there is no overlap in the estimation window).

[please insert table 20 about here]

Eventually, I assess whether the results on the hedging effectiveness are robust to the modifications of time horizon, data frequency or regression interval. As table 21 shows, this can be generally confirmed. Since the results do not vary much for different time horizons, only the results of the two year time horizon (for weekly returns) and the four year time horizon (for monthly returns) will be shown. The ex post filtering reduces the variance at least by 3.18% and at most by 5.83%. No matter if the forecasting period is one, two or three years, the variance of the hedged returns remains on average always higher compared to the unhedged returns.

[please insert table 21 about here]

6.2 Control variables and lagged exposure

The market return is widely used as control variable when estimating exchange rate exposures and allows to control for different kind of macroeconomic or other market wide shocks. Some other studies instead, or additionally, include factors of the Fama French asset pricing model, such as Makar and Huffman (2013), where they incorporate the factors for the value (HML) and size (SMB) premium in their model.

I run regression model (55) including the HML and SMB factors.[58] The coefficients are close to zero for both factors (the size premium SMB being significant at 5% level though) and hardly contribute to the coefficient of determination in this case. The fact, that these results are virtually the same as in the basic setting, indicate that the volatility of the exposure would not be affected by the incorporation of the Fama French factors neither.

I also include size as additional control variable in regression model (55), as e.g. suggested in (Bodnar and Wong, 2003). The variable is created by categorizing the total assets on the basis of deciles into a scale from 1 (small

[58]The data for value and size premiums have been downloaded from the homepage of K. French (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/). Since those data are only available at a monthly frequency, the exchange rate exposure is estimated with monthly returns in this case.

companies) to 10 (large companies). The size coefficient is significant at the one percent level, but the magnitude and significance of the exposures against the EUR and USD are not affected.

Size might also be a relevant determinant of the exchange rate exposure, since larger companies have generally more possibilities to operationally and financially hedge their exposure (see e.g. Bodnar and Wong (2003) or Hutson and Stevenson (2010)). I thus include the size variable in regression (59), but the results do not show any significant difference between small and large firms regarding their exposure. Again, the volatility of the exposure is not affected, because their estimation is based on firm-by-firm regressions and including size as control variable in this case does not change the results, since there is very low variation of size categories within firms.

It is possible that market inefficiency leads to a lagged effect of exposure into stock prices, see e.g. Doidge et al. (2006). I therefore examine regression model (55) with the one week lagged exchange rate and market returns as independent variables. The coefficients for the exposure against the EUR, USD and also the market returns are generally still significant, but much lower (just 6.5% significant exposures against the EUR and 4.5% against the USD compared to 10.3%, resp. 10.6% without the lagged variables). I thus find no evidence that lagged independent variables would be better in explaining exchange rate exposures and its time-variation.

7 Conclusion

This study examines the time-variation of exchange rate exposures of Swiss firms and how this volatility affects hedge effectiveness. While there exist a wide range of studies about the currency exposure, few of them focus on the time-variation of the exposure. This study explores this aspect and goes one step further by investigating the consequences of a volatile exposure on the hedge effectiveness.

First, I find that Swiss firms are significantly exposed to exchange rate movements, especially to the Euro. 24% of the sample firms show a statistically significant sensitivity towards currency movements of the Euro and 26% against the USD.

Second, I provide evidence that the exchange rate exposure is not constant over time for most firms. For the majority of observations, the exchange rate exposure at a point in time t is significantly different from the one at $t-1$. This is a first key result, since most previous studies about the currency exposure do not assess its volatility. One consequence of a time-varying exposure is that it leads to difficulties when trying to hedge the exposure based on the observation of historical data.

Third, I explore the hedging aspect in detail. I show that the hedge effectiveness is reduced due to the time-varying exposure. This can in some cases even lead to an increased stock return variance for hedged positions compared to unhedged ones. For example, estimating the currency exposure based on the data of the two past years and using the regression coefficient as hedge ratio for the stock returns in the next 12 months, leads to a variance which is on average 0.30% higher compared to the unhedged returns. An even longer forecasting horizon than 12 months increases the risk of counterproductive hedging.

I also have briefly investigated whether the volatility of the currency exposures can be explained by firm-specific determinants or by macroeconomic variables. The former do only explain a small portion of the variance in the exposures, while the latter seem to significantly drive them. Further analyzing how this patterns could be used to improve hedge effectiveness lies beyond the scope of this study, but would be a possible path for future research. Beside of the hedging, a time-varying exchange rate exposure can also be relevant in the contracting theory, which might be another interesting aspect for further research.

Appendix A: Definitions of the variables

Variable name:	Abbr.:	Definition:
FX return	$X^{CHF/EUR}$	$X_t^{CHF/EUR} = ln(\frac{(CHF/EUR)_t}{(CHF/EUR)_{t-1}})$
FX return	$X^{CHF/USD}$	equivalent to $X^{CHF/EUR}$
FX return	$X^{CHF/HKD}$	equivalent to $X^{CHF/EUR}$
FX-index return	X^{index}	$X_i^{index} = \sum_{j=EUR,USD,HKD} \frac{Net\ sales_{i,j}}{Net\ sales_i} * X^{CHF/j}$
Stock return	R_i	$R_{i,t} = ln(\frac{TRI_{i,t}}{TRI_{i,t-1}})$, where $TRI_{i,t}$ is the firm's total return index obtained from Datastream
Market return	R^M	$R_t^M = ln(\frac{SPI_{i,t}}{SPI_{i,t-1}})$
Foreign sales	FS	$FS_j = \frac{Net\ sales\ in\ region\ j}{Total\ net\ sales}$
Foreign assets	FA	$FA_j = \frac{Assets\ in\ region\ j}{Total\ assets}$
FX derivatives	DIV	$\frac{contract\ value\ of\ outst.\ FX\ derivatives}{Total\ assets}$
EBIT margin	$EBIT$	$\frac{EBIT}{Total\ net\ sales}$
Diversification	DIV	number of reported geographical segments with at least 10% of net sales
GDP growth	GDP	$ln(\frac{GDP_t}{GDP_{t-1}})$
Term spread	TS	Yield on 10yr Swiss confederation bond − 3 month LIBOR CHF

Appendix B: Correlation matrix

Panel A:	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
1. $X^{CHF/EUR}$	1.0000													
2. $X^{CHF/USD}$	.0052	1.0000												
3. $X^{CHF/HKD}$	.1203	.8530	1.0000											
4. R^M	.2426	.1334	.2151	1.0000										
5. Sales Switzerland	-.0004	-.0107	-.0095	-.0001	1.0000									
6. Sales Europe	.0337	-.0180	-.0209	.0079	-.7090	1.0000								
7. Sales Americas	-.0273	-.0058	-.0315	.0098	-.5842	.0817	1.0000							
8. Sales Asia	-.0163	.0457	.0673	-.0206	-.4784	-.0087	.1623	1.0000						
9. Assets Switzerland	-.0093	-.0084	-.0083	.0106	.6527	-.4627	-.3554	-.2904	1.0000					
10. Assets Europe	.0373	.0210	.0261	-.0094	-.4591	.5184	.0783	.1778	-.8067	1.0000				
11. Assets Americas	-.0307	-.0462	-.0730	.0086	-.4776	.1806	.6206	.0985	-.5354	.0672	1.0000			
12. Assets Asia	-.0094	.0179	.0311	-.0149	-.4012	.1350	.1754	.4671	-.4736	.1205	.2978	1.0000		
13. DIV	.0406	-.0011	.0073	.0165	-.2048	.1732	.0468	.1538	-.1682	.0939	.1585	.2085	1.0000	
14. EBIT margin	.0547	.0171	0366	.0340	-.0282	-.0182	.1128	.0229	.1233	-.2361	.1504	.0332	-.0530	1.000
Panel B:	1.	2.	3.	4.	5.	6.								
1. $X^{CHF/EUR}$	1.0000													
2. $X^{CHF/USD}$	.1703	1.0000												
3. $X^{CHF/HKD}$	.1834	.9903	1.0000											
4. R^M	.3491	.1381	.1324	1.0000										
5. GDP	.2915	.0291	.0419	.4918	1.0000									
6. TS	.0594	-.1818	-.1688	.0923	.0893	1.0000								

Panel A: The table shows the correlation coefficients among the exchange rate, the market return and the firm-specific variables. Different from table 11, the variables in this table are measured at a yearly frequency. Panel B: The table shows the correlation coefficients among the exchange rate, the market return and the macroeconomic variables. Different from table 11, the variables in this table are measured at a quarterly frequency.

Tables and figures

Table 9: Standard deviations of hedged returns

	Hedge ratio		
realized exposure γ_t	$h=0$	$h=1$	$h=-1$
$\gamma_{2012-2013}=-0.02$	**.01817**	.01864	.01890
$\gamma_{2008-2009}=+1.04$	.03673	**.03504**	.04035
$\gamma_{1999-2000}=-1.03$	.02425	.02574	**.02378**

This table shows the standard errors of unhedged ($h=0$) and hedged returns ($h=1$ and $h=-1$) for the stock returns of the firm 'Jungfraubahn Holding AG'. The returns are computed as $R_t^h = R_t^u - h * X_t^{EUR}$.
The realized exposures γ_t are the estimates from the regression 57: $R_{j,t} = \alpha_{j,t} + \sum_{i=1}^{n} \gamma_{i,j,t} X_{i,t} + \beta_{j,t} R_t^M + \varepsilon_{j,t}$

Table 10: Descriptive statistics

	N	Mean	Std dev.	Min	Max
$X^{CHF/EUR}$	834	-.00036	.0069	-.026	.026
$X^{CHF/USD}$	834	-.00041	.0139	-.035	.032
$X^{CHF/HKD}$	834	-.00039	.0137	-.034	.033
stock return R_i	74763	.00069	.0475	-.391	.371
market return R^M	834	.00052	.0217	-.067	.059
$FS_{Switzerland}$	1471	.2554	.3424	0	1.00
FS_{Europe}	1471	.4319	.2401	0	.87
$FS_{Americas}$	1471	.1555	.1496	0	.71
FS_{Asia}	1471	.1100	.1395	0	.74
$FA_{Switzerland}$	1127	.2554	.3424	0	1.00
FA_{Europe}	1127	.4359	.2401	0	1.00
$FA_{Americas}$	1127	.1201	.1374	0	.61
FA_{Asia}	1127	.0596	.0839	0	.40
FXD	1021	.0563	.1017	0	.54
DIV	1474	2.4299	.8723	1.00	4.00
EBIT	1485	.0898	.0776	0	.34
GDP	63	.0050	.0061	-.0196	.02
TS	64	1.2160	.7036	-.3895	2.52

The table shows the number of observations (N), the mean value (Mean), the standard deviation (Std dev.), the minimum value (Min) and the maximum value (Max) for each variable. The definition of the variables is provided in appendix A. The sample period lasts from 1999 to 2014 and contains weekly data for the return variables, yearly data for the firm-specific variables and quarterly data for the macroeconomic variables. The sample comprises 100 firms from the SPI with overall 74'763 weekly return observations.

Table 11: Correlation matrix

	1.	2.	3.	4.
1. $X^{CHF/EUR}$	1.0000			
2. $X^{CHF/USD}$	.3434	1.0000		
3. $X^{CHF/HKD}$	.3078	.9102	1.0000	
4. R^M	.3216	.1855	.2014	1.0000

The table shows the correlation coefficients among the exchange rate and the market return variables. The data is measured at a weekly frequency. Appendix 7 additionally shows the correlation coefficients for the firm-specific and macroeconomic variables.

Table 12: Descriptive statistics on the estimated exposures

		N	mean	sd	min	max
$\widehat{\gamma}_{EUR}$	All industries	1376	.3703	1.0598	-7.89	6.83
	Basic Materials	104	.4425	1.0062	-2.50	4.31
	Industrials	644	.4032	1.0545	-3.96	6.83
	Consumer Goods	183	.1561	.8909	-2.64	4.91
	Health Care	191	.3575	1.2654	-7.89	4.40
	Consumer Services	129	.3608	.8967	-2.86	3.33
	Telecommunications	15	-.0441	.3428	-.47	.64
	Utilities	34	.1947	.7816	-1.51	1.95
	Technology	76	.7173	1.3137	-2.32	4.42
$\widehat{\gamma}_{USD}$	All industries	1376	-.0904	.4535	-3.87	4.51
	Basic Materials	104	-.1869	.3530	-1.01	.76
	Industrials	644	-.1421	.4456	-3.87	1.58
	Consumer Goods	183	-.0054	.3940	-1.10	2.69
	Health Care	191	-.0910	.6037	-2.59	4.51
	Consumer Services	129	-.0907	.3910	-1.41	.94
	Telecommunications	15	.1221	.2570	-.38	.69
	Utilities	34	-.0361	.3532	-1.00	.78
	Technology	76	.0359	.4208	-1.00	.93

The table shows the number of estimates (N), the mean (mean) and the standard deviation (sd) of the estimates, as well as the minimum value (min) and the maximum value (max).
The regression model used to generate these estimates is model (55):
$R_{j,t} = \alpha_{j,t} + \sum\limits_{i=EUR,USD} \gamma_{i,j,t} X^{CHF/i} + \beta_{j,t} R^M + \varepsilon_{j,t}$

Table 13: Exchange rate exposures - pooled OLS

	model (1)				**model (2)**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$X^{CHF/EUR}$	.9171**	.8819**			.2674**	.1888**		
	(17.66)	(17.27)			(9.08)	(7.21)		
$X^{CHF/USD}$	-.0507**		.1138**		-.1204**		-.0788**	
	(-2.90)		(6.40)		(-7.17)		(-5.19)	
X^{index}				.6790**				.0510
				(12.86)				(1.27)
R^M					.6997**	.6949**	.7236**	.7261**
					(18.74)	(18.65)	(18.93)	(19.23)
Intercept	.0010**	.0010**	.0007**	.0009**	.0003	.0004	.0002	.0003
	(4.08)	(4.11)	(2.93)	(3.48)	(1.34)	(1.44)	(.95)	(1.15)
N	74763	74763	74763	72484	74763	74763	74763	72484
R^2	.0175	.0173	.0011	.0085	.1084	.1073	.1071	.1118

The column 'model (1)' estimates the regression model 54: $R_j = \alpha_j + \sum_{i=EUR,USD} \gamma_{i,j} X^{CHF/i} + \varepsilon_j$

The column 'model (2)' estimates the regression model (55): $R_j = \alpha_j + \sum_{i=EUR,USD} \gamma_{i,j} X^{CHF/i} + \beta_j R^M + \varepsilon_j$

The table shows the estimated coefficients and the t-statistics in parentheses.
Standard errors are clustered by firm to control for heteroskedasticity and to allow for serial correlation within the firm's observations.
* and ** denote statistical significance at the 5% and 1% level, respectively (two-tailed test).

Table 14: Exposures resulting from firm-by-firm regressions

	model (1)			**model (2)**		
	$\gamma_{i,j} > 0$	$\gamma_{i,j} < 0$	%	$\gamma_{i,j} > 0$	$\gamma_{i,j} < 0$	%
Panel A:						
$X^{CHF/EUR}$	99	1		82	18	
thereof sign. at 5%	86	0	86.0%	22	2	24.0%
thereof sign. at 1%	68	0	68.0%	6	1	7.0%
$X^{CHF/USD}$	34	66		20	80	
thereof sign. at 5%	4	11	15.0%	2	24	26.0%
thereof sign. at 1%	2	4	6.0%	1	11	12.0%
R^M				99	1	
thereof sign. at 5%				97	0	97.0%
thereof sign. at 1%				93	0	93.0%
Panel B:						
X^{index}	90	5		50	45	
thereof sign. at 5%	57	0	57.0%	3	4	7.0%
thereof sign. at 1%	43	0	43.0%	1	1	2.0%
R^M				100	0	
thereof sign. at 5%				97	0	97.0%
thereof sign. at 1%				94	0	94.0%

The column 'model (1)' estimates model 54: $R_j = \alpha_j + \sum_{i=EUR,USD} \gamma_{i,j} X^{CHF/i} + \varepsilon_j$

The column 'model (2)' estimates model (55): $R_j = \alpha_j + \sum_{i=EUR,USD} \gamma_{i,j} X^{CHF/i} + \beta_j R^M + \varepsilon_j$

The regressions are run for each firm separately. Standard errors are corrected for heteroskedasticity. The table shows the number of positive and negative regression coefficients resulting from this procedure. The third column shows the percentage of significant regression coefficients.
Panel A shows the results for the independent variables $X^{CHF/EUR}$ and $X^{CHF/USD}$. Panel B shows the results for the independent variable X^{index}.

Table 15: Exposures resulting from firm-by-firm rolling regressions

	Model (1)			Model (2)		
	$\gamma_j > 0$	$\gamma_j < 0$	%	$\gamma_j > 0$	$\gamma_j < 0$	%
$X^{CHF/EUR}$	1190	185		868	506	
thereof sign. at 5%	540	6	39.7%	111	31	10.3%
thereof sign. at 1%	309	0	22.5%	42	7	3.6%
$X^{CHF/USD}$	601	775		562	814	
thereof sign. at 5%	95	151	17.9%	40	106	10.6%
thereof sign. at 1%	39	68	7.8%	15	43	4.2%
R^M				1317	58	
thereof sign. at 5%				943	2	68.7%
thereof sign. at 1%				808	0	58.7%

The column 'model (1)' estimates model 54: $R_{j,t} = \alpha_{j,t} + \sum_{i=EUR,USD} \gamma_{i,j,t} X^{CHF/i} + \varepsilon_{j,t}$

The column 'model (2)' estimates model (55): $R_{j,t} = \alpha_{j,t} + \sum_{i=EUR,USD} \gamma_{i,j,t} X^{CHF/i} + \beta_{j,t} R^M + \varepsilon_{j,t}$

The regressions are run for each firm separately over a period of two years by a rolling regression approach. The interval between the regressions is one year. Standard errors are corrected for heteroskedasticity.
The table shows the number of positive and negative regression coefficients resulting from this procedure. The third column shows the percentage of significant regression coefficients.

Table 16: Results on the stability of the exposures

			Firms with a p-value of lower than					
			$\delta_{i,j} = 1$			$\delta_{i,j} = 0$		
	Mean δ_i	Mean R^2	.1	.05	.01	.1	.05	.01
$\widehat{\gamma}_{EUR,t-1}$	.5048	.3167	67%	47%	27%	69%	59%	38%
$\widehat{\gamma}_{USD,t-1}$	.4676	.2909	67%	51%	26%	62%	57%	32%

The regression model used is 58: $\widehat{\gamma}_{i,j,t} = \delta_{i,j}\widehat{\gamma}_{i,j,t-1} + \varepsilon_{i,j,t}$
The regressions are run for each firm separately. The dependent variable is the estimated exchange rate exposure $\gamma_{i,j}$ obtained from regression model 57, the independent variables is the dependent variable lagged by one year. The sample contains 100 firms.
'Mean $\delta_{i,j}$' shows the average regression coefficient over the entire sample, 'Mean R^2' the average R-squared value, the rejection rates show the percentage of firms for which the hypothesis $\delta_{i,j} = 1$, resp. $\delta_{i,j} = 0$ has been rejected using a Wald test.
Standard errors are corrected for heteroskedasticity.

Table 17: Determinants of the exchange rate exposure

	CHF/EUR			CHF/USD		
	Coeff.	sd	t-stats	Coeff.	sd	t-stats
$\hat{\gamma}_{i,j} > 0$:						
FS	.5029	.3012	(1.67)	.2566	.2176	(1.18)
FA	-.4108	.2420	(-1.70)	-.2199	.1953	(-1.13)
DIV	.0003	.0602	(.01)	-.0122	.0245	(-.50)
EBIT	-2.8702**	.7754	(-3.70)	-.9564**	.3207	(-2.98)
FXD	.5879	.5583	(1.05)	-.0658	.1358	(-.48)
Intercept	1.0626**	.1729	(6.14)	.3899**	.0894	(4.36)
N	449			270		
R^2	.0704			.0612		
$\hat{\gamma}_{i,j} < 0$:						
FS	-.5642*	.2393	(-2.36)	-.0531	.1444	(-.37)
FA	.3990	.2081	(1.92)	.2650	.1839	(1.44)
DIV	.1075*	.0506	(2.12)	-.0260	.0244	(-1.06)
EBIT	1.3396	.8181	(1.64)	.3804	.2312	(1.65)
FXD	-.0382	.4716	(-.08)	-.3321	.2175	(-1.53)
Intercept	-.8568**	.1989	(-4.31)	-.3239**	.0789	(-4.11)
N	275			454		
R^2	.0480			.0259		

The regression model used is (59): $\widehat{\gamma}_{i,j} = \alpha_{i,j} + \delta_{0,i,j} FS_{i,j} + \delta_{1,i,j} DIV_j + \delta_{2,i,j} EBIT_j + \delta_{3,i,j} FA_{i,j} + \delta_{4,i,j} FXD_j + \varepsilon_{i,j}$
The dependent variable is the estimated exchange rate exposure $\hat{\gamma}_{i,j}$ obtained from regression model (57), the independent variables are described in appendix A.
The table shows the estimated regression coefficient (Coeff.), the standard deviation (sd) and the t-values (t-stats).
Standard errors are clustered by firm to control for heteroskedasticity and to allow for serial correlation within a firm's observations.
* and ** denote statistical significance at the 5% and 1% level, respectively (two-tailed test).

Table 18: Macroeconomic determinants of exchange rate exposure

	γ_0		γ_{GDP*XR}		γ_{TS*XR}	
	$\hat{\gamma}_0$	t-stats	$\hat{\gamma}_1$	t-stats	$\hat{\gamma}_2$	t-stats
X^{EUR}	1.89**	6.05	-81.78**	-3.84	-1.05**	-5.76
$X^{CHF/USD}$	-.51**	-4.50	39.21**	4.55	.10	1.52
R^M	1.06**	13.59	3.15	.64	.15**	3.18
$X^{CHF/EUR}$	1.20**	4.35	-17.51	-.90	-.86**	-5.23
R^M	1.07**	13.39	-6.96	-1.37	.18**	3.86
$X^{CHF/USD}$	-.18*	-1.81	16.93*	2.21	-.02	-.40
R^M	1.30**	16.55	-16.64**	-4.13	.02	.44

The regression model used is (6): $R_{j,t} = \alpha_{j,t} + \gamma_0 R_t^M + \gamma_0^{EUR} X_{EUR,t} + \gamma_0^{USD} X_{USD,t} + \sum_{k=1}^{K} (\gamma_k^{EUR} + \gamma_{k,j}^{EUR}) IV_{k,t-1} X_{EUR,t} + \sum_{k=1}^{K} (\gamma_k^{USD} + \gamma_{k,j}^{USD}) IV_{k,t-1} X_{USD,t} + \sum_{k=1}^{K} (\beta_k + \beta_{k,j}) IV_{k,t-1} R_t^M + \varepsilon_{j,t}$
The dependent variable is the estimated exchange rate exposure $\hat{\gamma}_{i,j}$ obtained from regression model (57). The independent instrument variables (IV) are GDP and TS as described in appendix A.
The table shows the estimated regression coefficient (γ), the t-values (t-stats).
Standard errors are clustered by firm to control for heteroskedasticity and to allow for serial correlation within a firm's observations.
* and ** denote statistical significance at the 5% and 1% level, respectively (two-tailed test).

Table 19: Comparison of unhedged and hedged stock return variances

		ex post			1-year-ahead		
	N	R^u	R^h	%	R^u	R^h	%
all industries	100	.00231	.00222	3.63%	.00227	.00227	-.30%
Basic Materials	7	.00188	.00179	5.16%	.00196	.00195	.56%
Industrials	46	.00221	.00213	3.96%	.00218	.00215	1.01%
Cons. Goods	13	.00187	.00183	2.41%	.00181	.00183	-1.09%
Health Care	15	.00306	.00297	2.94%	.00308	.00318	-3.20%
Cons. Services	9	.00186	.00179	3.69%	.00184	.00187	-1.54%
Telecomm.	1	.00055	.00053	3.42%	.00046	.00048	-4.64%
Utilities	3	.00196	.00188	4.08%	.00171	.00167	2.34%
Technology	6	.00372	.00353	5.06%	.00348	.00346	.55%
		2-year-ahead			3-year-ahead		
all industries	100	.00217	.00223	-2.57%	.00204	.00209	-2.37%
Basic Materials	7	.00196	.00200	-1.84%	.00192	.00198	-3.20%
Industrials	46	.00203	.00206	-1.40%	.00189	.00193	-2.24%
Cons. Goods	13	.00177	.00180	-1.44%	.00169	.00174	-3.50%
Health Care	15	.00316	.00345	-9.03%	.00303	.00315	-3.80%
Cons. Services	9	.00172	.00171	.30%	.00161	.00170	-5.65%
Telecommun.	1	.00041	.00041	-1.85%	.00039	.00041	-4.17%
Utilities	3	.00177	.00184	-3.84%	.00192	.00172	10.13%
Technology	6	.00307	.00295	4.07%	.00266	.00261	1.80%

This table compares the variances of the undhedged returns (R^u) and the hedged returns (R^h). The column (%) shows the hedge effectiveness ($\frac{Var(R^u) - Var(R^h)}{Var(R^u)}$). The column (N) shows the number of firms per industry.

Table 20: Exposure volatility for different time horizons and intervals

DF	TH	RI	$\delta_{i,j} = 1$ γ_{EUR}	$\delta_{i,j} = 1$ γ_{USD}	$\delta_{i,j} = 0$ γ_{EUR}	$\delta_{i,j} = 0$ γ_{USD}
W	1 yr	6m	80	83	63	65
W	2 yrs	6m	33	37	97	93
W	3 yrs	6m	26	22	94	96
W	1 yr	12m	88	90	10	12
W	2 yrs	12m	47	44	55	52
W	3 yrs	12m	34	22	77	73
M	3 yrs	6m	44	23	90	90
M	4 yrs	6m	30	18	91	96
M	5 yrs	6m	22	15	91	96
M	3 yrs	12m	33	23	58	70
M	4 yrs	12m	35	23	69	77
M	5 yrs	12m	27	19	72	78

DF = data frequency, W = weekly, M = monthly, TH = time horizon, RI = Regression interval, 6m = 6 months, 12m = 12 months.
The regression model used is 58: $\widehat{\gamma}_{i,j,t} = \delta_{i,j}\widehat{\gamma}_{i,j,t-1} + \varepsilon_{i,j,t}$
The regressions are run for each firm separately. The dependent variable is the estimated exchange rate exposure $\gamma_{i,j}$ obtained from regression model 57, the independent variables is the dependent variable lagged by one year. The sample contains 100 firms.
The numbers in the table show the percentage of firms for which the hypothesis $\delta_{i,j} = 1$, resp. $\delta_{i,j} = 0$ has been rejected using a Wald test with a significance level of 5%.

Table 21: Stock return variances for different regression intervals

	ex post R^u	ex post R^h	ex post %	1-year-ahead R^u	1-year-ahead R^h	1-year-ahead %
weekly returns:						
6 month	.00214	.00208	3.18%	.00203	.00204	-.20%
12 months	.00231	.00222	3.63%	.00227	.00227	-.30%
monthly returns:						
6 month	.01029	.00971	5.63%	.00973	.00988	-1.53%
12 months	.01030	.00970	5.83%	.00973	.00976	-.36%
	2-year-ahead			3-year-ahead		
weekly returns:						
6 month	.00196	.00204	-4.20%	.00201	.00204	-1.10%
12 months	.00217	.00223	-2.57%	.00204	.00209	-2.37%
monthly returns:						
6 month	.00977	.01020	-4.42%	.00961	.01000	-4.05%
12 months	.00977	.01015	-3.89%	.00961	.00100	-3.99%

The time horizon used is two years for the weekly data and four years for the monthly data. All variances are computed as in table 19.

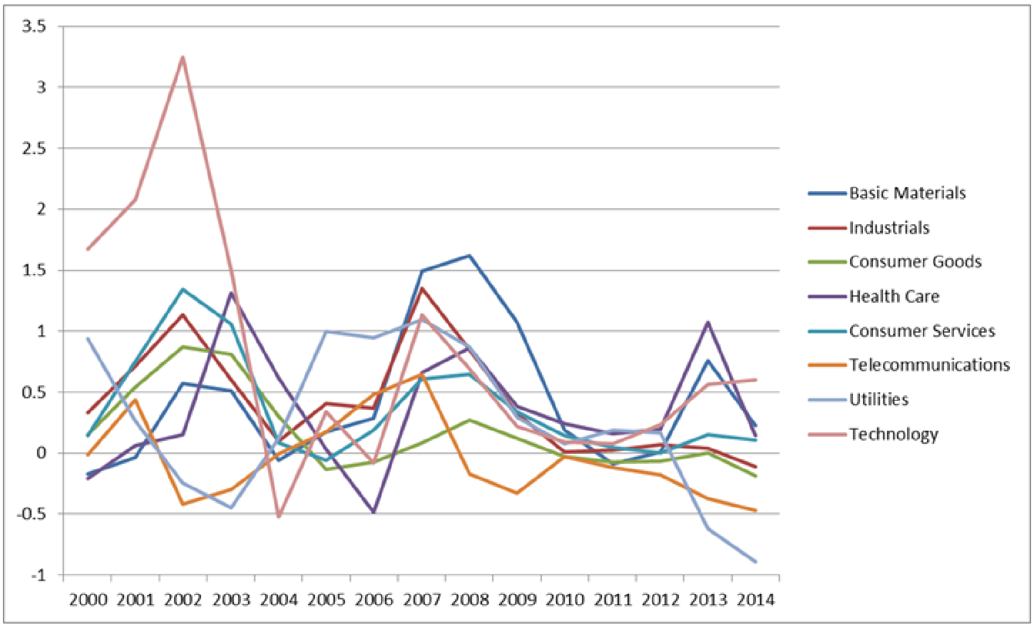

Figure 1: Average exposures against the EUR per industry

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Curriculum vitae

Personal Data

Name:	Lars Kabitz
Date of Birth:	09.08.1984

Education

2012 - 2017	PhD studies, University of Zurich, Department of Business Administration
2013 - 2014	Swiss Certified Accountant, EXPERTsuisse, Zurich
2009 - 2011	Master of Arts in Accounting and Finance, University of Fribourg (CH)
2005 - 2008	Bachelor of Arts in Management, University of Fribourg (CH)

Work experience

since 2016	Financial Controller, AdNovum Informatik AG, Zurich
2011 - 2016	Auditor, Ernst&Young AG, Bern
2010 - 2011	Undergraduate research assistant, University of Fribourg
2009	Internship as auditor, KPMG AG, Fribourg
2007 - 2008	Substitute teacher at secondary school, OS Tafers, Fribourg